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New Evidence on Using Expert Ratings to Proxy for Wine Quality in Climate Change Research

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New Evidence on Using Expert Ratings to Proxy for Wine Quality in Climate Change Research

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Abstract: This paper provides new evidence on the validity of using product-level expert wine-scoring data as a proxy for wine quality in climate change research, using nearly 15,000 Bob Campbell ratings of New Zealand wines from 2002 to 2016. We examine two to three regression models for each of the seven most prominent varieties in New Zealand, each with 8-12 treatments. We look for a positive, concave relationship between the expert score and the growing season temperature that gives an optimal temperature value that is plausible given research from other countries. We find mixed results – only 56% of our results are consistent with expectation and give a plausible optimal temperature and 27% are also significant. However, when we "collapse" the data by region, variety and year, essentially constructing vintage scores from our product-level data, we find that all results are consistent with expectation and plausible and 53% are statistically significant despite the sample size after collapsing becoming very small. We conclude that there is great potential in using vintage data constructed from expert-rating data for individual wines for climate change research.

Keywords: Weather, climate change, wine score, wine quality

JEL Classifications: C32, Q54

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1. Introduction

It is an undeniable fact that the wine regions around the world are affected by climate change[1]. The quality of fine wine in particular depends on the quality of the grapes, which is affected by the climatic conditions during the wine-growing season (Tate, 2001, Hannah *et al.*, 2013 and Mozell and Thach, 2014). Climate change has increased the average global temperature by more than a degree Celsius since 1880, and the warming of the temperature is picking up pace (Turner *et al.,* 2009). Higher temperatures lead to grapes ripening earlier, which affects the composition of the grapes, ultimately changing the quality of the wine. In the Coonawarra region of Australia, for example, Cabernet Sauvignon can now be harvested 45 days earlier than before (Webb et al., 2007, 2008, 2012). Depending on the current climate and the expected change in climate in a given wine region, climatic changes may have positive or negative implications on the wine quality (Tate, 2001, van Leeuwen and Darriet, 2016). This paper contributes to the knowledge about the effect of climate change on the quality of wine by examining New Zealand data.

To understand the effects of climate on wine quality, it is necessary to have a good measure of or a proxy for the quality of wine. A pioneer in the field, Ashenfelter, used auction prices to measure the quality of a small number of Bordeaux Chateaux wines. Known as the "Bordeaux equation", the model attributes higher wine quality to higher growing-season temperature, higher dormant-season rainfall and lower harvest rainfall. It has been successful in predicting prices of mature wines, often surpassing the predictive power of the expert wine tasters who make predictions of the quality of a young wine when at maturity (Ashenfelter et al., 1995; Ashenfelter, 2008, 2010[2]). Byron and Ashenfelter (1995) used same equation to successfully predict mature-auction prices of a single Australian wine, Penfold's Grange Hermitage. Wood and Anderson (2006) used Langton's auction data for three icon Australian red

[1] According to the Intergovernmental Panel on Climate Change [IPCC] (2007), climate change is a statistically significant variation in either the mean state or the variability of climate that persists for an extended period, typically decades or longer.
[2] Ashenfelter (2008, 2010) provide peer-reviewed and updated results that first appeared in Ashefelter's online blog, Liquid Assets, in Ashenfelter (1986,1987a, 1987b, 1990).

wines. They concluded that the price variations of the Penfold's Grange and St Henri can best be modelled with a linear function while Henschke's Hill of Grace fits best a quadratic model of the growing-season temperature and that the average daily temperature and the average daily maximum temperature give approximately the same results.

In theory, prices are more likely to reflect the quality of the wine in a given vintage when prices vary from vintage to vintage, both up and down, and when consumer information is reflected in the prices. These conditions are certainly met with fine mature-wine auctions where fluctuations in demand lead to immediate fluctuations in prices. Ashenfelter (2010, as referenced in Ashenfelter and Storchmann, 2016) found that auction prices of mature Bordeaux wines produced by the same winemaker from fruit grown on the same plot of land can vary by a factor of 20 or more from year to year depending on the quality of the vintage. Where mature-wine auctions are not commonplace, one could use cellar-door prices or recommended retail prices. These prices, however, tend not to vary from vintage to vintage, especially not downwards, making them potentially problematic to use prices as the proxy for quality in climate change research. However, Haeger and Storchmann (2006) successfully used the recommended retail prices of 451 California and Oregon Pinot Noir rated in the Wine Spectator in 1998-2003 and found that the relationship between a price and the growing-season temperature is a positive, concave function.

An alternative way to measure the quality of the wine is to use expert ratings of the wine. Because it takes a lot of training to recognise a good-quality wine, let alone variations in the quality between the vintages, the average wine consumer relies on the expert opinion of others (Storchmann, 2012). While the ability and integrity of professional wine tasters have been questioned by a number of researchers in wine economics (see for example Hodgson, 2008; Goldstein, 2008; and Reuter, 2009), expert opinion is used in wine research to proxy quality as it is often the best available option. Some of this research uses both prices and expert opinion to gauge the ability of experts to predict the wines that will ultimately be the most valuable. Ashenfelter and Jones (2013) found that experts' ratings add some predictive power to regressions that estimate auction prices as functions of weather variables, potentially justifying the use of expert ratings to proxy quality in a situation where no data on auction prices exists.

Most research using expert ratings use vintage ratings rather than ratings for individual wine, including Ashenfelter and Jones discussed above. Vintage ratings are favoured because there is often more agreement about it than about ratings of individual wines and because this avoids the complications that arise due to variations in winemaking affecting wine quality. Jones *et al*. (2005) used the Sotheby's vintage ratings in their study of the effect climate on wine quality for the dominant varieties grown in important wine regions around the world. They found a significant concave relationship between growing-season temperature and vintage rating for some varieties and regions while for others the relationship was either found to be insignificant or convex. The results of Jones *et al*. suggest that wine regions in Europe are currently facing the optimal growing season temperatures for the grapes traditionally grown in those regions and that, by 2050, the wine quality in Europe may well have started to decline unless wineries are able to adapt by growing new varieties or adopting new wine-making techniques. However, their findings suggest that the relationship between climate and the quality of wine is less clear for the New World wine regions. Other research that has used vintage ratings includes Grifoni et al. (2006) and Corsi and Ashenfelter (2019), both of which studied the effects of weather on some prestigious North-Western Italian wines. While Grifoni et al. found that higher vintage scores were associated with higher temperatures and lower rainfall during the growing season, Corsi and Ashenfelter found weak results at best, with only summer rain having a significant coefficient with the predicted sign. Baciocco *et al.* (2014) used consensus ranking of vintages to study the effect of weather on Bordeaux red and sweet white wine vintage rankings. They found that while the growing season temperature correlated positively and the growing season rain negatively with the quality of both wine types, the optimal conditions during ripening, verison and dormancy were different. Sadras et al. (2007) used the vintage ratings of 24 Australian wine regions over 25 years and found that the increase in the average temperature has had a positive effect on the ratings of red vintages and reduced the ratings' variability from year to year, but these results were not found for the vintages of white wines. Jones and Davis (2000) used Bordeaux vintage ratings to study the two main red Bordeaux varieties - Merlot and Cabernet Sauvignon - and found that the variations in vintage quality were mostly derived from the variation in the characteristics of Cabernet Sauvignon.

There are also a small number of papers that, like us, use expert ratings of individual wines to proxy the quality of wines. Ramirez (2008) used Wine Spectator scores of all Napa Valley Cabernet Sauvignon to study the effect of weather on ratings and prices. He found that, while about 70% of the variation in prices could be explained by weather, only about 3% of the variation in expert ratings was explained by weather. He also found that many of the coefficient signs were inconsistent with expectation or not statistically significant, especially in the quadratic functions that he found to be rife with issues with multicollinearity given that linear terms and quadratic terms are correlated by definition. Oczkowski (2016) used ratings from Halliday (2014) to study the weather-rating and the rating-price relationships for a number of Australian varieties. He found consistent negative effects of harvest rain. The expected concave relationship for the growing-season temperature was found to be significant for Cabernet Sauvignon, Chardonnay, Merlot, Pinot Noir, Sauvignon Blanc and Shiraz while the effect was found to be exactly the opposite for Riesling and Semillon.

This paper presents new evidence about the validity of using expert ratings of individual wines to proxy for wine quality in climate change research, using Bob Campbell's wine scores as a proxy for the wine quality. Bob Campbell is one of the most influential wine scorers in New Zealand and holds the coveted Master of Wine qualification. Furthermore, his rating database is by far the most extensive - our dataset, that includes the seven varieties with most ratings from 2002-2016, has nearly 15,000 observations. Following Oczkowski (2016), we estimate the link between the quality and weather variables separately for each variety to capture that variety's unique relationship with weather. For this reason, we also limit our analysis to the wines that have a single variety. Also in line with Oczkowski, we pool observations from the seven wine regions together to maximise the number of observations available for each variety, which implicitly assumes that the *function* that links weather to quality remains the same across regions although the weather varies between them.

We start with a standard OLS model but we also use a fixed-effects model with product-level fixed effects. High-quality wines are often produced with grapes from old vines, planted in a terroir that is best-suited for the varietal and pruned and watered optimally. The winemaker's skill, the quality and age of the barrels used for the fermentation and ageing as well as the length of time the wines are aged in a barrel and other wine-making techniques contribute to quality. Using product-level fixed effects is a method to control for all the variability in the *underlying quality* that is driven by all factors outside of weather. Most previous studies have not had to worry about this aspect, having focused on the best-quality wines produced under strictly controlled conditions where variation in quality is therefore more likely to reflect variations in weather. The use of vintage scores also removes this issue.

We assume that the true relationship between climate and wine quality is a positive, concave function of temperature, indicating that there is a maximum temperature beyond which we would expect the wine quality to deteriorate. For us to have confidence in our regression results, therefore, we need to find a positive coefficient for the linear temperature term and a negative coefficient for the quadratic term. Also, we need the predictions for the optimal temperature levels, derived from the regression coefficients, to be reasonable and in line with findings from other countries for the grape varieties that we investigate, although some variation can be expected due to differences in wine-making styles. We would also like the temperature-related regression coefficients to be statistically significant and to have a reasonably high R^2 value.

Much of the existing research findings suggest that the key climatic variables affecting wine quality is the growing–season temperature and that the quality improves with dormant-season rainfall but goes down with harvest rain. While studies that focus on predicting the value of a mature wine using weather data tend to use a linear model, the concave function of temperature is in line with the understanding that increases in temperature will eventually start to reduce the quality of wines, if they have not already done so, and is thus more suitable when looking for long-term effects of climate change on the quality of wine. We want to see if our product-level dataset is able to produce robust results to support climate change research.

The quality of the wines included in our study vary immensely between the products, which is perhaps the best highlighted by the price range from $7 to $350. The wines that are produced in a way that optimises the variables that are under the viticulturist's and wine-maker's control are at *the quality possibilities frontier* that maps the weather variables to the best possible quality given the weather. For such a wine, any improvements in weather are likely to see a better-quality wine and vice versa. However, it is it is less clear if this is the case for mass-produced wines where the winemaker's goal is to produce an affordable wine with a large yield. If not, then having these wines in the sample could bias the results. Using product-level fixed effects will not solve this issue because it assumes common coefficients for the weather variables. We use two different treatments to restrict our sample to wines of better quality to see if this is an issue. The first method limits the sample to wines with higher prices. The second method uses the 2017 Suckling list of top-100 wines from New Zealand to limit our sample to all the available vintages of the wines that are on that list. We find better results when focusing on the more expensive wines for Chardonnay, Merlot and Sauvignon Blanc and the top-100 wines for Syrah, but for other varieties, such as Pinot Noir, the results do not improve and may deteriorate.

Last, we move to testing the model with "vintage data", obtained from our product-level data by averaging the scores and associated weather variables by each variety, region and year, to see if using a constructed vintage score improves the ability to identify the underlying link between wine quality and weather. On the plus side, using vintage scores can remove some subjectivity from the individual scores, which could lead to better precision in the findings. It also allows us to compare our results to others, such as Jones and Davis (2000), Jones *et al*. (2005) and Corsi and Ashenfelter (2019), who used vintage scores. Furthermore, the method reconciles some of the differences in the explanatory power that have been found by researchers using vintage scores and those using product-level, micro data where the former performs consistently better. On the minus side, creating this "macro" dataset greatly reduces the size of the dataset, which in itself should have a detrimental effect on the precision of the results.

Our results when using the micro data are mixed – the coefficients for the key temperature variables are as expected in 56% of the treatments but significant in just 27% of them. The OLS model performs significantly better than the FE model. We find that the results vary greatly for different grape varieties, consistent with what others have found. Our best results are found for Chardonnay, Sauvignon Blanc and Pinot Gris. The red varieties perform worse than the white varieties, but they each have at least one treatment that give us potentially useful results. This is somewhat different from what Sadras et al. (2007) found for Australia where the link between weather and quality was found for red varieties only and no doubt reflects the different climatic conditions in Australia compared to New Zealand. When using the constructed vintage data, however, we get results that are consistent, plausible and in many cases very precise despite having only a small number of observations. The coefficients for the key temperature variables are as expected in 100% of the treatments and significant in 53% of them. We therefore conclude that there is great potential in using vintage data constructed from product-level data to help understand the impact of climate change on the quality of wine.

The remainder of this paper is organised as follows. Section 2 describes the data sources and variables used in the regression analysis. Section 3 presents the methodology and models and Section 4 presents the results. Section 5 concludes.

2. Data and Variables

The key variables required for our research include the wine rating data that we collected from Bob Campbell's website and the weather data that we collected and transformed from National Institute of Water and Atmospheric Research [NIWA]. We also needed geographic coordinates to match each vineyard to the closest NIWA weather station.

We collected the ratings of New Zealand wines rated by Bob Campbell from 2002 to 2016 in our dataset. While the dataset goes back to 2000, we did not include observations from 2000-2001 when a very small number of wines were being rated compared to subsequent years. At the time of data collection in 2019, the dataset was not yet complete for vintages beyond 2017 and therefore our dataset ends in 2016. All the wines in the database were rated on a 100-point scale[3] although there are no wines rated below 84 in the dataset. We focus on the seven most prominent varieties - Pinot Noir, Syrah, Chardonnay, Merlot, Sauvignon Blanc Riesling and Pinot Gris and dropped the observations of other varieties and blended wines. Our panel dataset is

[3] Campbell originally scored using a 20-point system but later switched to the 100-point scale used by Gourmet Traveller Wine as well as Robert Parker, using a mathematical model to convert his earlier scores into ones that are compatible with the 100-point system.

imbalanced with the number of different wines each year varying from 285 in 2002 to 1,587 in 2009, giving us a total of 14,821 observations.

We collected the GPS coordinates of the wineries from the New Zealand Wine Growers' Association website and of the weather stations from the NIWA Research website to allow us to match the vineyards with the closest weather station. The obvious limitation of our approach is that, while we use the weather data of the closest weather station, the distance to the closest weather station varies and the data may not perfectly fit with the growing conditions of the vineyard. It is also possible that the vineyard or the block where the specific grapes were grown has a microclimate that differs from the climate of the closest station even when the weather station is close. What we have, however, is the closest possible approximation of each vineyard's weather that is available to us. In the small number of cases where the GPS coordinates of the vineyard were not known but we knew the general winegrowing region, we matched the winery with the average weather data from the wine region's weather stations.

The data available on the NIWA website includes daily data on the maximum temperature, the minimum temperature, relative humidity and rainfall. While relative humidity clearly affects the quality of the grapes, we did not use relative humidity in our regressions due to encountering issues with multicollinearity, given that relative humidity and rainfall are closely correlated. Most other research that we refer, including the seminal research of Ashenfelter, omits relative humidity, and we suspect it is for the same reason. The exceptions to this are Byron and Ashenfelter (1995) and Wood and Anderson (2006) who include the relative humidity variable but find that it does not explain the quality of wine.

The vintage of a wine is defined by the year of the harvest and the weather data that is matched with that wine is collected for the twelve months immediately prior to the harvest. Thus, New Zealand being a Southern Hemisphere country, the wine calendar starts in May after the previous harvest and ends in April the year of the harvest. The dormant season runs from May to September and the growing season from October to April. The temperature variables are expressed as average daily values and the rain variables are aggregates. This approach is similar to that taken by Ashefelter (2008, 2010)[4]. The variables used are described in Table 1.

Table 1: A description of the variables used in the research.

Variables	Description of the Variables
score	Wine score from Bob Campbell's website[5]
tgrowing *tgrowingmax* *tgrowingdiff*	Average temperature* in October-April (growing season) Average maximum temperature in October-April (growing season) Average daily difference between the maximum and the minimum temperature in October-April (growing season)
rdormant	Aggregate rainfall (mm) for May-September (dormant season)
rharvest	Aggregate rainfall (mm) for March-April (harvest season)

* The daily temperature observation used to construct this variable is averaged from the daily maximum and minimum values, making this essentially the average average temperature.

Table 2 contains the summary statistics of the climatic variables used in the research for New Zealand as a whole and for its seven main wine regions, organised from North to South, for years 2002, 2016 and 2002-2016. It also shows results of a regression where the average weather observation per region is regressed on the time trend and where coefficient for the trend variable measures the annual growth in the climatic variable. The last column in Table 2 presents the 2022 forecast for each weather variable, obtained with the regression results[6]. The forecast value is useful to compare that region's current weather to what our models tell us is the optimal weather for a given variety, a discussion that we have in Section 4. Given that the weather fluctuates around the trend from year to year, it is better to use the forecasted current value instead of the current value itself. It is clear from Table 2 that the minimum temperature falls as one moves

[4] Ashenfelter also used a variable that measured the age of the wine from the harvest because he was investigating the quality of mature Bordeaux wines. The wines in our database are generally rated soon after release, when they are available for purchase and we did not record the age of the wine at tasting when constructing the dataset. In hindsight, having had the tasting date would have been a great addition to the dataset.
[5] http://bobcampbell.nz/ which directs to https://www.therealreview.com/wines/
[6] Specifically, the 2022 forecast is equal to the constant + trend coefficient *(2022-2002).

Table 2: Summary statistics of the different temperature variables and the rainfall variables for 2002, 2016 and 2002-2016 including trend and 2022 prediction, for New Zealand and main wine regions.

	2002		2016		2002-2016		Regression results 2002-2016			
Region and Variables	mean	sd	mean	sd	mean	sd	Constant	trend	R2	2022
New Zealand										
tgrowing	15.69	1.099	16.00	0.851	15.44	0.927	15.22***	0.0320	0.181	15.86
tgrowingmax	19.89	1.220	21.47	1.189	20.56	1.326	19.91***	0.0865***	0.582	21.64
tgrowingmin	11.26	2.099	10.45	2.092	10.21	1.986	10.35***	-0.0149	0.028	10.05
dormantrain	335.8	160.1	310.2	119.1	387.3	165.1	369.8***	1.444	0.007	398.7
harvestrain	59.42	35.83	82.83	64.54	73.83	49.89	69.30***	0.736	0.013	84.02
Auckland										
tgrowing	17.99	0.0649	18.59	0.295	17.82	0.492	17.38***	0.0706***	0.469	18.79
tgrowingmax	21.65	0.0349	22.27	0.552	21.56	0.647	21.01***	0.0869***	0.492	22.75
tgrowingmin	14.34	0.0898	14.92	0.178	14.09	0.537	13.76***	0.0544**	0.336	14.85
dormantrain	597.8	27.40	631.4	60.35	567.3	86.87	525.6***	7.782	0.169	681.2
harvestrain	115.4	5.888	27.58	4.820	63.21	50.85	89.80***	-2.590	0.048	37.99
Hawke's Bay										
tgrowing	16.19	0.462	16.62	0.500	16.01	0.573	15.69***	0.0437*	0.253	16.57
tgrowingmax	18.65	0.411	19.75	0.855	18.87	0.826	18.36***	0.0686**	0.341	19.73
tgrowingmin	12.95	0.146	12.95	0.0524	12.47	0.372	12.27***	0.0302	0.146	12.87
dormantrain	488.6	41.60	334.9	80.47	515.0	95.16	544.1***	-5.211	0.073	439.8
harvestrain	44.75	15.96	38.24	19.63	74.09	51.87	84.10***	-1.051	0.009	63.08
Wairarapa										
tgrowing	16.27	0.487	16.77	0.494	16.11	0.631	15.82***	0.0377	0.179	16.57
tgrowingmax	19.72	0.414	20.64	0.712	19.90	0.884	19.65***	0.0307	0.083	20.26
tgrowingmin	12.83	0.893	12.91	0.784	12.32	1.126	11.98***	0.0448*	0.232	12.88
dormantrain	308.6	41.09	271.5	60.03	463.2	135.8	454.4***	-0.145	0.000	451.5
harvestrain	36.44	21.16	24.42	19.90	69.58	43.38	75.06***	-0.674	0.005	61.58
Nelson										
tgrowing	15.93	0.0638	16.60	0.0727	15.78	0.350	15.47***	0.0507**	0.366	16.48
tgrowingmax	20.13	0.103	21.51	0.140	20.42	0.484	19.99***	0.0684**	0.401	21.36
tgrowingmin	11.71	0.283	11.67	0.340	11.12	0.467	10.91***	0.0350	0.158	11.61
dormantrain	380.7	6.068	347.8	52.60	452.0	100.8	408.4***	4.426	0.045	496.9
harvestrain	80.45	22.54	286.1	33.64	116.9	63.89	69.31**	7.731*	0.252	223.9
Marlborough										
tgrowing	15.40	0.138	15.99	0.0633	15.43	0.336	15.13***	0.0399**	0.271	15.92
tgrowingmax	20.36	0.574	21.88	0.711	21.03	0.879	20.45***	0.0738**	0.398	21.93
tgrowingmin	10.44	0.823	10.10	0.838	9.837	0.847	9.805***	0.00576	0.006	9.920
dormantrain	243.0	79.20	367.7	57.16	401.6	139.8	325.8***	8.353	0.097	492.9
harvestrain	93.38	20.25	120.4	4.032	91.01	44.33	83.06***	1.199	0.020	107
Canterbury										
tgrowing	13.81	0.396	14.76	0.282	14.15	0.585	13.56***	0.0749***	0.577	15.06
tgrowingmax	18.85	0.0907	20.78	0.217	19.84	0.596	19.06***	0.0937***	0.512	20.94
tgrowingmin	8.778	0.692	8.731	0.429	8.459	0.721	8.056***	0.0557**	0.341	9.169
dormantrain	194.6	0.430	246.0	9.574	302.3	94.74	239.6***	6.196	0.095	363.5
harvestrain	40.92	6.089	58.61	8.681	44.59	25.34	37.28***	1.391	0.072	65.11
Otago										
tgrowing	14.49	0.763	14.96	0.501	14.52	0.811	14.13***	0.0514***	0.503	15.15
tgrowingmax	21.00	1.376	22.52	1.123	21.65	1.410	20.97***	0.0861***	0.639	22.69
tgrowingmin	7.997	0.154	7.393	0.135	7.395	0.366	7.285***	0.0163	0.056	7.611
dormantrain	130.9	40.58	124.8	52.82	161.1	70.54	140.2***	2.385	0.069	187.9
harvestrain	15.15	8.802	20.24	7.813	31.85	17.41	23.54***	1.050	0.119	44.54

from Auckland, the northernmost wine region, to Otago, the southernmost wine region and, with the exception of Otago, the same is true for the average temperature. However, there is no similar ranking of the daily maximum temperature, and in fact the two warmest daily averages are for Auckland and Otago, the northernmost and the southernmost wine regions, respectively. All wine regions but Wairarapa have experienced a significant increase in the growing season average temperature of 0.04-0.07 degrees per year and the growing season maximum temperature of 0.07-0.09 degrees per year, while the minimum temperature has increased significantly in Auckland, Wairarapa and Canterbury only. Nelson that has experienced a mildly significant increase in the harvest rain but other rainfall variables have been stationary. This suggests that climate change in New Zealand, at the moment at least, is mostly manifested in the positive trend of the daily maximum temperature.

Table 3: Summary statistics of wine scores by variety and region, including trend, for 2002, 2016 and 2002-2016.

	2002			2016			2002-2016			Regression		
Scores by variety	**N**	**mean**	**sd**	**N**	**mean**	**sd**	**N**	**mean**	**sd**	**Constant**	**trend**	**R^2**
Pinot Noir	86	88.70	4.090	252	91.12	3.829	4,233	90.25	3.710	88.42***	0.238***	0.708
Syrah	21	90.19	4.143	44	90.80	3.764	851	91.03	3.710	89.26***	0.184**	0.334
Chardonnay	105	88.31	3.520	178	90.81	3.870	2,518	89.94	3.642	88.28***	0.243***	0.866
Merlot	37	86.59	3.295	19	88.32	3.801	484	88.11	3.464	86.84***	0.167**	0.264
Sauvignon Blanc	9	85.78	3.153	217	90.34	3.560	3,087	89.58	3.478	87.20***	0.287***	0.717
Riesling	22	87.86	3.106	89	91.75	3.425	1,870	90.53	3.533	88.28***	0.301***	0.839
Pinot Gris	5	88.40	4.099	131	89.82	3.098	1,778	89.73	3.257	88.44***	0.149***	0.583
Total	285	88.23	3.777	930	90.68	3.683	14,821	90.01	3.606	88.19***	0.235***	0.812
	2002			**2016**			**2002-2016**			**Regression**		
Scores by region	**N**	**mean**	**sd**	**N**	**mean**	**sd**	**N**	**mean**	**sd**	**Constant**	**trend**	**R^2**
Auckland	23	85.52	2.609	26	90.73	3.996	543	89.29	3.936	86.53***	0.408***	0.784
Hawke's Bay	85	88.09	3.747	136	89.68	3.930	2,499	89.32	3.691	87.74***	0.204***	0.544
Wairarapa	24	87.75	3.814	92	91.64	3.206	1,168	91.18	3.493	89.10***	0.259***	0.633
Nelson	13	86.46	3.178	44	89.91	3.753	1,049	89.11	3.467	86.86***	0.304***	0.790
Marlborough	76	88.93	3.649	409	90.21	3.680	5,949	89.85	3.538	88.56***	0.164***	0.544
Canterbury	19	86.95	2.571	66	91.08	3.343	1,122	90.10	3.612	88.10***	0.258***	0.643
Otago	45	90	4.051	157	92.26	3.187	2,491	91.02	3.339	88.95***	0.260***	0.829
New Zealand	285	88.23	3.777	930	90.68	3.683	14,821	90.01	3.606	88.19***	0.235***	0.812

Table 3 shows the summary statistics of the wine scores by grape and by region in 2002, 2016 and overall. It also shows the regression results where the annual average score per variety or per region, respectively, is regressed on the time trend. The coefficient for the trend variable measures the annual growth in the scores of the variety or the region, respectively. The top half of the table shows that all grape varieties have experienced significant rating growth over our study period. The average wine in the dataset was rated at 90 points. The bottom half of the table shows that wines from all regions have grown in quality over the study period although the growth has been the slowest for the most important wine region in New Zealand in terms of size, Marlborough.

Table 4: Number of wines in each category per variety and number of wine varieties scored per region, 2002-2016.

Score	**Pinot Noir**	**Syrah**	**Chardonnay**	**Merlot**	**Sauvignon Blanc**	**Riesling**	**Pinot Gris**	**Total**
83	10	2	13	3	2	1	3	34
84	589	82	332	127	488	205	247	2070
85	143	23	120	46	148	62	51	593
86	60	14	52	10	51	29	27	243
87	143	26	120	23	124	57	70	563
88	71	12	77	12	55	26	32	285
89	767	139	438	94	643	335	381	2797
90	423	80	234	49	327	178	211	1502
91	277	44	152	26	198	145	153	995
92	526	110	343	40	418	287	273	1997
93	288	75	176	21	193	125	125	1003
94	213	34	106	9	129	82	67	640
95	513	131	274	22	288	272	127	1627
96	144	50	49	2	21	37	7	310
97	48	23	25	0	2	18	2	118
98	15	4	5	0	0	10	2	36
99	3	2	1	0	0	1	0	7
100	0	0	1	0	0	0	0	1
Total	4233	851	2518	484	3087	1870	1778	14821
Region	**Pinot Noir**	**Syrah**	**Chardonnay**	**Merlot**	**Sauvignon Blanc**	**Riesling**	**Pinot Gris**	**Total**
Auckland	24	123	218	49	47	5	77	543
Hawke's Bay	166	591	807	325	310	86	214	2499
Wairarapa	508	35	147	2	175	165	136	1168
Nelson	251	15	204	4	210	184	181	1049
Marlborough	1412	62	823	99	2123	733	697	5949
Canterbury	351	22	162	3	137	292	155	1122
Otago	1521	3	157	2	85	405	318	2491
New Zealand	4233	851	2518	484	3087	1870	1778	14821

Table 4 provides further background information about the sector by tabulating the scores for each variety as well as counting the varieties per region in the dataset. The top half of the table shows that just one wine[7] received a score of 100 in the dataset and just seven wines have scored 99. The scores start at 83 and the mode of the wine scores is 89. The bottom half of Table 4 is useful for identifying the most important varieties for each region. In Auckland and Hawkes Bay these are Chardonnay and Syrah, but in Hawke's Bay Merlot and Sauvignon Blanc are also important. Wairarapa and Nelson focus on Pinot Noir, Marlborough on Sauvignon Blanc and Pinot Noir and Canterbury and Otago on Pinot Noir and Riesling, but the other white varieties are also quite important for these five regions.

Table 5 gives summary statistics on the wine prices in the dataset, for each variety and each region. Pinot Noir and Syrah are the two most expensive varieties in the dataset, followed by Chardonnay. The standard deviation is also the highest for these three varieties. While the bottom prices of these varieties are similar to the less expensive varieties, the top prices are much higher at $225 for Pinot Noir, $350 for Syrah and $175 for Chardonnay, compared to $75-$100 for the other four varieties.

Table 5: Summary statistics of wine prices by variety, 2002, 2016 and 2002-2016.

	2002				**2016**				**2002-2016**			
Variety	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**	**mean**	**sd**	**min**	**max**
Pinot Noir	33.39	9.046	16	60	43.96	24.21	16	150	39.08	18.89	11.95	225
Syrah	37.78	15.48	19.95	70	43.22	25.55	19.95	150	41.86	25.31	9.950	350
Chardonnay	25.97	7.925	11.95	59.95	35.32	18.96	15	150	29.40	14.04	8.990	175
Merlot	29.39	10.06	15.95	55	28.93	10.78	15.99	49.99	26.05	11.30	11.95	100
Sauvignon Blanc	23.88	6.064	18.95	35.95	23.25	6.398	14	59.99	22.46	6.410	6.950	95
Riesling	19.82	2.579	16	24.95	27.59	8.288	12.99	70	25.15	7.673	8.990	100
Pinot Gris	23.22	9.339	15.95	33.75	23.68	6.271	13.99	60	24.32	6.180	9	75
All	28.81	10.02	11.95	70	32.73	18.91	12.99	150	30.24	15.78	6.950	350

[7] For those interested, this was the 2014 Moutere Chardonnay from the Neudorf Vineyard, located in the Nelson wine region.

3. Methodology and Models

In this section we present the regression models that we use to test the validity of using the product-level dataset of Bob Campbell wine scores as a proxy of wine quality in climate change research. We use two models for six of the varieties, where the main explanatory variable of interest is the average temperature during the growing season. For Pinot Gris, we also report a third model where the key explanatory variable is the maximum temperature as this model explains the quality ratings of Pinot Gris better than the average temperature.

When using product-level data, we use both OLS and product-level fixed-effects model. The definition of product is a single wine label. This means that many wineries have multiple products of a particular variety released each year.[8] The models we estimate are all quadratic in the key temperature variable investigated to tease out the optimal temperature that is essential for climate-change research. In the first model we regress the wine score with the average growing-season temperature and its quadratic term, the total dormant-season rain and the harvest rain. The hypotheses here are that the score is a positive but concave function of the growing-season temperature, a positive function of the rain during the dormant season and a negative function of the rain that coincides with harvest. Equation (1) summarises Model 1:

$$Score = \beta_0 + \beta_1 tgrowing + \beta_2 tgrowing^2 + \beta_4 rdormant + \beta_5 rharvest + e. \quad (1)$$

In Model 2, we add *tgrowingdiff*, the difference between the maximum and minimum temperatures, to replicate the work of Oczkowski (2016). Contrary to Oczkowski's hypothesis that this term should have a negative sign, our hypothesis is that this term is positive for the cool-climate varieties that are often said to benefit from cool night-time temperatures and warm daytime temperatures. In New Zealand, these varieties are Sauvignon Blanc, Pinot Noir and Riesling, judging by the revealed preference of what is grown in cooler climates. To keep our

[8] For example, Felton Road Wines has 12 wine labels, or products, in the dataset, including four different labels of Chardonnay, five of Pinot Noir and three of Riesling, but not all of these were made and tasted each year

results comparable with Model 1, we also include *rdormant*, which is not included in Oczkowski. Equation (2) summarises model 2:

$$Score = \beta_0 + \beta_1 tgrowing + \beta_2 tgrowing^2 + \beta_3 tgrowingdiff + \beta_4 rdormant + \beta_5 rharvest + e. \quad (2)$$

For Pinot Gris only, we also present findings from Model 3 where the variable *tgrowing* is replaced by *tgrowingmax*. We do this because this model best fits to explain the quality ratings of this variety:[9]

$$Score = \beta_0 + \beta_1 tgrowingmax + \beta_2 tgrowingmax^2 + \beta_3 tgrowingdiff + \beta_4 rdormant + \beta_5 rharvest + e. \quad (3)$$

We run each model with and without a trend variable. The trend variable is included in a small number of papers in the literature, including Ramirez (2008). Because global warming implies that, on the average, temperatures are on the rise, a trend variable could simply pick up the effect of temperature rising and thus introduce multicollinearity. Our results suggest that the trend variable is usually highly significant, improves the R^2 values quite considerably and does not usually interfere with the sign and significance of the coefficient estimates for the temperature variables. Using of two models that are identical in other ways but the presence of the trend variable helps explain why studies that use a trend tend to have a higher R^2 values than studies that do not.

We have two further treatments that are meant to limit the sample to better-quality wines only that are more likely to be on the quality-possibilities frontier where we can with more confidence expect improvements in weather to improve wine quality. First, we include only wines that have had a price of at least $50 during the sample period for Pinot Noir, Syrah and

[9] For space constraints, the results of this model are not presented for the other varieties for which it performed poorly.

Chardonnay, the most expensive varieties in New Zealand, and at least $30 for other varieties[10]. Second, we use the 2017 Suckling list of top-100 wines from New Zealand (Suckling, 2017), a list gathered by a critic independent from Bob Campbell, to limit our sample to all the available vintages of the wines that are on that list[11]. The top-100 treatment is used to study only the three varieties that feature more than twice on the Suckling list – Pinot Noir, Syrah and Chardonnay.

Our last treatment is to "collapse" the product-level data by year, variety and region, inspired by a lot of the existing work that uses vintage ratings instead of ratings of individual wines but in the absence of readily available vintage ratings for New Zealand. This method gives us regional weather variables that are weighted averages of the variable values for the different weather station matched to the region's wineries, where the weights are the number of wines associated with each station. The vintage model has the regional annual average rating of a variety as the independent factor and the regional average weather variables as explanatory factors.

Because our models are quadratic, neither of the coefficients for the linear and quadratic terms used alone give us a clue about where we are in terms of climate change affecting wine quality. Expressing marginal effects calculated at current regional temperature is one way to understand whether the region has reached its optimal wine-growing weather for a variety or if the quality is still expected to rise with further increases in temperature. Marginal effects are found by taking the first-order differential of the rating equation (1), (2) or (3) with respect to the temperature variable and then inserting the current values of the temperature variable of interest into the derivative. For example, the marginal effect of Model 1 is:

$$\text{Marginal effect} = \frac{\partial Score}{\partial tgrowing} = \beta_1 + 2\beta_2 tgrowing. \qquad (4)$$

[10] These dollar amounts are arbitrary cut-off points that aim to weigh the pros and cons of having only good wines included and not losing too many wines in the sample to lose statistical significance. We have tried a number of different cut-off points, and none performed better than this one.
[11] Only 84 of the Suckling top-100 wines are in our dataset. This is mostly because our exclusion of blended wines, which means that the highly-rated Bordeaux blends are not included.

While we expect to find a positive coefficient for the linear term, β_1, and a negative coefficient for the quadratic-term, β_2, we have no hypothesis for the sign of the marginal effect. In fact, one of the main points of our research agenda is to identify this sign. If we have a positive marginal effect, the results indicate that we can expect wine scores to go up at least for the time being as temperatures rise, while a negative overall marginal effect indicates that the current temperature is already past the optimal level.

Due to having a larger number of models and treatments as well as large variation in current temperature between different regions, we have opted to report the implied optimal temperature for each variety instead of reporting regional marginal effects. We can use (4) to calculate the expected optimal temperature, or the temperature where the marginal effect switches from positive to negative:

$$tgrowing^* = -\frac{\beta 1}{2\beta 2}. \tag{5}$$

This gives us an easy way to compare the current temperatures to our prediction of the optimal temperature. If the optimal temperature in (5) is larger than the current temperature in a given region, the marginal effect in (4) is positive, and we can expect the average quality of the wine to increase for the time being with further increases in temperature. Similarly, if the optimal temperature is below the current temperature in the region, the marginal effect is negative and we have already surpassed the point where climate change starts to deteriorate average wine quality for the given variety and region. After we discuss the main findings in Section 4, we discuss where the optimal temperatures for key varieties in each region are with respect to that region's current temperature.

4. Results and Discussion

In this section, we report and discuss the results of our regression models. For each variety, we have two to three models, each with 10-14 different treatments. The full results are available in Appendix Tables 1-7. Here our focus is on summary results, found in Tables 6-8, where we present coefficient estimates and significance levels for the linear and quadratic temperature variables, the R^2 value of the regression and the predicted optimal temperature from (6). Table 6 presents the results for Pinot Noir, Syrah and Chardonnay, the varieties for which we report the results of 14 treatments because they include the top-100 treatments, Table 7 presents the results for Merlot, Sauvignon Blanc and Riesling for which we report the results of 10 treatments, while Table 8 presents the results for Pinot Gris for which we present the results of three models with 10 treatments each.

In Tables 6-8, we have used colour codes to help the reader digest the results. The cells highlighted in grey are the ones that have results contrary to expectations in terms of the sign of the linear and quadratic temperature terms. The white cells indicate results that are consistent with expectations but the coefficients for the key temperature variables are not significant. The red cells indicate results that are consistent with expectations but they have insignificant coefficients with an optimal temperature prediction that is clearly not plausible. The green cells indicate that the coefficients are not only consistent with hypothesis but also significant – the darker the green the more significant the coefficients[12]. The purpose of this section is to learn what models and treatments work the best in giving us plausible results, how sensitive those results are to the treatments used and how these results vary between the seven varieties studied.

We can see from Table 6 that out of the 12 treatments for Pinot Noir that use product-level data, only one – the fixed effects model with trend for the full sample - gives us results that are consistent with theory, with statistically significant coefficients and a plausible optimal temperature values. However, we get great results with the constructed vintage data where results for both Models 1 and 2, with and without a trend, have significant coefficients and plausible predictions for optimal temperature. The vintage regressions also have significantly higher R^2 value than any of the results with product-level data. The "green" and vintage results suggest that the optimal growing season average temperature for Pinot Noir is 13.99-15.50. The temperature difference variable in Model 2, where significant, is positive, which indicates

[12] Dark green: either both terms are significant at 1% or one is significant at 1% and the other at 5%; Medium green: either both terms are significant at 5% or one is significant at 5% and the other at 10%; Light green: either both terms are significant at 10% or one is significant at 10% and the other is not significant.

that Pinot Noir *improves* in quality when the difference between the daily maximum and minimum temperatures grows. While this is against the hypothesis made by Oczkowski (2016), it is consistent with the understanding that cool-climate wines thrive with larger temperature differences.

The Syrah results in Table 6 also show that the results are mostly inconsistent with hypothesis or consistent but insignificant. The only significant results for the product-level data are the OLS and OLS with trend results for Model 1 for wines above $50. When significant, the temperature difference variable in Model 2 is negative, which is consistent with this variety being a warm-climate variety. The best R^2 values are found in the top-100 treatment, suggesting that the weather-quality relationship for Syrah is present the strongest with the best wines. The fact that the coefficients are not significant in these regressions is most likely due to having a small number of observations – we have just 61 observations over eight products. While for this variety the collapsed data does not give significant coefficients, the results have coefficient signs that are consistent with hypothesis and optimal temperature estimates that are plausible. The "green" and vintage results predict the optimal temperature to be 16.14-17.08. This band is quite narrow, with the upper bound being two degrees less than that predicted by Jones (2015). We suspect that this reflects the style of the New Zealand Syrah being optimised for a cooler climate than what is the norm in many other wine regions. Thus, for regions where temperatures are higher than the optimal levels should be able to adapt the style of the wine to improve wine scores as temperatures rise.

The results for Chardonnay in Table 6 are promising. Model 1 has significant coefficients with expected signs for all but the top-100 treatment, and Model 2 performs almost as well. Using the over $50 wines only improves the predictive power of the models. The temperature difference variable in Model 2, when significant, is always positive, which indicates that this is a cool-climate variety. The vintage data regressions have significant coefficients in one treatment only but all have coefficient signs that conform to hypotheses. The optimal temperature is predicted to be 15.32-17.87. Both the fact that this range is significantly higher than that for Pinot Noir and that Chardonnay is mostly grown in the north suggest that Chardonnay is a warm-climate variety, contradicting the earlier finding from the positive temperature difference

Table 6: Summary results for Pinot Noir, Syrah and Chardonnay.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	VARIABLES	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
	Treatment	all	all	all	all	>=$50	>=$50	>=$50	>=$50	top100	top100	top100	top100	vintage	vintage
	tgrowing	1.162	1.738	0.886	3.988	-0.970	2.072	-4.860	-2.127	-13.12***	-12.42***	-5.783	-3.653	9.000**	5.060
Pinot Noir	tgrowingsq	-0.0248	-0.0513	-0.00800	-0.143*	0.0503	-0.0588	0.200	0.0725	0.446***	0.417***	0.216	0.114	-0.300**	-0.180*
Model 1	R-squared	0.043	0.112	0.010	0.077	0.025	0.164	0.041	0.146	0.065	0.115	0.033	0.158	0.248	0.523
	tgrowing*	23.39	16.95	55.38	13.99	9.652	17.61	12.18	14.66	14.73	14.88	13.41	16.01	14.98	14.02
	tgrowing	-3.104*	0.141	0.889	4.014*	-5.207*	2.805	-4.883	-1.786	-15.51***	-11.75**	-6.389	-4.017	10.62***	6.090*
Pinot Noir	tgrowingsq	0.122**	0.00403	-0.00923	-0.141*	0.195*	-0.0839	0.200	0.0654	0.525***	0.395**	0.227	0.122	-0.343***	-0.208**
Model 2	tgrowingdiff	0.257***	0.0947***	0.0648	-0.139	0.186***	-0.0306	0.0231	-0.279	0.0699	-0.0194	0.435	0.237	0.353***	0.171
	R-squared	0.056	0.114	0.010	0.077	0.034	0.164	0.041	0.148	0.068	0.115	0.041	0.160	0.312	0.537
	tgrowing*	12.71	-17.51	48.18	14.21	13.35	16.71	12.21	13.65	14.77	14.88	14.09	16.48	15.50	14.62
	tgrowing	4.627	3.081	-0.548	-1.613	12.55***	10.73**	-12.28	-12.96*	53.27	44.44	26.52	17.52	7.188	7.322
Syrah	tgrowingsq	-0.129	-0.0867	0.0354	0.0516	-0.382***	-0.332**	0.407*	0.401*	-1.628	-1.358	-0.796	-0.574	-0.210	-0.220
Model 1	R-squared	0.031	0.054	0.018	0.037	0.044	0.075	0.037	0.087	0.261	0.270	0.143	0.319	0.122	0.253
	tgrowing*	17.98	17.77	7.742	15.63	16.41	16.17	15.09	16.15	16.36	16.36	16.66	15.25	17.08	16.66
	tgrowing	2.387	-0.569	-0.617	-1.529	7.560	4.253	-12.21	-12.91*	59.70	34.16	26.41	17.23	6.036	4.273
Syrah	tgrowingsq	-0.0609	0.0232	0.0370	0.0495	-0.232	-0.137	0.397*	0.397*	-1.865	-1.092	-0.800	-0.565	-0.177	-0.132
Model 2	tgrowingdiff	-0.123*	-0.193***	0.0548	-0.0760	-0.289***	-0.356***	0.569	0.251	-0.585***	-0.690***	0.550	-0.203	-0.112	-0.300**
	R-squared	0.034	0.061	0.018	0.037	0.068	0.110	0.043	0.088	0.518	0.590	0.156	0.320	0.126	0.282
	tgrowing*	19.59	12.26	8.328	15.45	16.29	15.48	15.38	16.25	16.01	15.64	16.51	15.25	17.04	16.14
	tgrowing	3.133***	2.569***	6.122**	5.996**	9.441**	9.086**	16.97**	16.08**	-0.998	-1.419	4.908	3.834	5.153	2.983
Chardonnay	tgrowingsq	-0.0877**	-0.079***	-0.179**	-0.196**	-0.272**	-0.273**	-0.491**	-0.502**	0.0379	0.0460	-0.144	-0.139	-0.153	-0.0954
Model 1	R-squared	0.012	0.087	0.013	0.042	0.050	0.224	0.079	0.206	0.010	0.071	0.008	0.089	0.040	0.519
	tgrowing*	17.87	16.19	17.12	15.32	17.34	16.64	17.29	16.02	13.15	15.43	17.09	13.77	16.81	15.63
	tgrowing	2.263	2.096*	5.930**	6.283**	15.70***	13.16***	14.07*	14.74*	-1.144	-1.443	1.863	1.953	6.365**	3.190
Chardonnay	tgrowingsq	-0.0582	-0.0630*	-0.174**	-0.204**	-0.456***	-0.392***	-0.413*	-0.465**	0.0457	0.0489	-0.0623	-0.0868	-0.186*	-0.101
Model 2	tgrowingdiff	0.167***	0.0942***	0.0677	-0.102	0.322***	0.209**	0.787	0.369	0.184*	0.0897	0.858**	0.558	0.290***	0.0404
	R-squared	0.022	0.090	0.013	0.042	0.084	0.238	0.093	0.209	0.035	0.076	0.038	0.101	0.109	0.520
	tgrowing*	19.45	16.64	17.08	15.42	17.20	16.77	17.03	15.86	12.52	14.76	14.95	11.26	17.10	15.79

variable. Jones (2015) suggests that the range of suitable climate for Chardonnay range from cool to warm climates, helping to reconcile this seeming inconsistency.

The results for Merlot in Table 7 show that the product-level results and consistent with expectation for one treatment only – OLS for the wines that are over $30. The vintage results do not have significant coefficients but again give coefficients that have a sign consistent with hypothesis. The optimal temperature estimates from range from 16.63-18.74, which fit within the optimal temperature band of Jones (2015) that is approximately 61-66 degrees Fahrenheit (16.11-18.9 degrees Celsius).

The results for Sauvignon Blanc in Table 7 show that the product-level data has great results for OLS with and without the trend for all the treatments, including the vintage regressions. Model 2 has consistently better explanatory power than Model 1 for this variety, and the coefficients for the difference variable are positive and highly significant, which is in line with this variety being a cool-climate variety that is grown mostly in the South Island. The explanatory power of the model improves when limiting the sample to wines of $30 or more and the best results are obtained with the vintage data. The "green" and vintage results predict an optimal temperature of 15.31-16.46 degrees.

The results for Riesling in Table 7 show that there are only four product-level treatments that give plausible and significant results, all using OLS. However, all the vintage results are consistent with hypothesis, highly significant and have the highest R^2 values. The "green" and vintage results predict the optimal temperature to be 14.52-16.06 degrees. The difference variable, when significant, is positive, consistent with Riesling being a cool-climate variety.

Last, Table 8 shows the summary results for Pinot Gris where we have added the results of Model 3 where quality is modelled as a function of the average daily maximum temperature instead of average daily average temperature. As stated earlier, this model performs poorly for the other varieties but is very successful in predicting wine quality for Pinot Gris when using OLS. The vintage results are again the best. The prediction for the optimal maximum temperature is 20.54-22.26, and the predictions for the optimal average temperature from models 1-2 is 14.97-16.68.

Table 7: Summary results for Merlot, Sauvignon Blanc and Riesling

	VARIABLES	(1) OLS all	(2) OLS trend all	(3) FE all	(4) FE trend all	(5) OLS >=$30	(6) OLS trend >=$30	(7) FE >=$30	(8) FE trend >=$30	(9) OLS vintage	(10) OLS trend vintage
Merlot Model 1	tgrowing	7.447	1.995	-0.234	-2.159	17.01**	10.25	11.86	20.00	7.910	6.332
	tgrowingsq	-0.213	-0.0536	0.0351	0.0756	-0.510**	-0.313	-0.308	-0.589	-0.220	-0.174
	R-squared	0.031	0.077	0.025	0.046	0.057	0.154	0.109	0.160	0.136	0.206
	tgrowing*	17.52	18.62	3.333	14.28	16.66	16.39	19.24	16.98	17.95	18.18
Merlot Model 2	tgrowing	7.347	0.580	-4.026	-4.868	18.90**	11.03	-10.93	-0.0262	7.115	3.853
	tgrowingsq	-0.209	-0.0103	0.147	0.158	-0.568**	-0.336	0.389	0.0283	-0.198	-0.103
	tgrowingdiff	-0.00565	-0.0724	0.832*	0.647	0.112	0.0431	1.859**	1.529	-0.0983	-0.260
	R-squared	0.031	0.078	0.038	0.054	0.060	0.155	0.155	0.190	0.140	0.236
	tgrowing*	17.54	28.27	13.69	15.45	16.63	16.39	14.06	0.462	18.00	18.74
Sauv Blanc Model 1	tgrowing	14.34***	11.76***	1.174	5.807	25.65***	24.16***	-10.52	11.51	9.286***	7.728**
	tgrowingsq	-0.451***	-0.381***	-0.0179	-0.191	-0.813***	-0.784***	0.365	-0.383	-0.291***	-0.252**
	R-squared	0.028	0.092	0.009	0.046	0.075	0.241	0.013	0.119	0.107	0.518
	tgrowing*	15.88	15.43	32.83	15.19	15.77	15.40	14.42	15.01	15.95	15.31
Sauv Blanc Model 2	tgrowing	10.71***	9.562***	0.593	5.447	22.32***	22.35***	-10.17	12.91	11.22***	8.727***
	tgrowingsq	-0.325***	-0.301***	-0.00189	-0.181	-0.698***	-0.718***	0.355	-0.424	-0.349***	-0.282***
	tgrowingdiff	0.418***	0.309***	0.119	0.0718	0.561***	0.349***	-0.0458	-0.168	0.282***	0.136*
	R-squared	0.079	0.118	0.009	0.046	0.179	0.276	0.013	0.120	0.177	0.533
	tgrowing*	16.46	15.87	156.8	15.04	15.99	15.57	14.33	15.22	16.08	15.48
Riesling Model 1	tgrowing	4.602**	6.485***	-0.880	4.314	6.207	9.035**	-6.629	-0.772	21.00***	14.63***
	tgrowingsq	-0.143**	-0.215***	0.0565	-0.143	-0.187	-0.291**	0.255	0.0218	-0.702***	-0.504***
	R-squared	0.019	0.128	0.023	0.082	0.026	0.116	0.033	0.173	0.241	0.694
	tgrowing*	16.06	15.06	7.788	15.11	16.61	15.50	12.99	17.72	14.95	14.52
Riesling Model 2	tgrowing	-1.118	3.869*	-1.004	4.202	1.613	6.974	-6.719	-0.903	18.68***	14.24***
	tgrowingsq	0.0541	-0.125*	0.0553	-0.142	-0.0305	-0.221	0.260	0.0286	-0.619***	-0.489***
	tgrowingdiff	0.391***	0.168***	0.261	0.164	0.265***	0.110	-0.0724	-0.109	0.313***	0.0730
	R-squared	0.053	0.134	0.024	0.083	0.045	0.119	0.033	0.173	0.296	0.697
	tgrowing*	10.34	15.54	9.076	14.78	26.46	15.79	12.93	15.77	15.10	14.56

Table 8: Summary results for Pinot Gris

	VARIABLES	(1) OLS all	(2) OLS trend all	(3) FE all	(4) FE trend all	(5) OLS >=$30	(6) OLS trend >=$30	(7) FE >=$30	(8) FE trend >=$30	(9) OLS vintage	(10) OLS trend vintage
	tgrowing	2.230*	2.178*	-2.200	-1.781	1.857	2.871	1.948	2.665	2.639	2.282
Pinot Gris	tgrowingsq	-0.0725*	-0.0727*	0.0828	0.0549	-0.0478	-0.0839	-0.0366	-0.0765	-0.0815	-0.0745
Model 1	R-squared	0.023	0.047	0.008	0.025	0.015	0.052	0.020	0.052	0.115	0.334
	tgrowing*	15.39	14.97	13.29	16.21	19.41	17.12	26.62	17.42	16.20	15.33
	tgrowing	1.543	1.665	-2.106	-1.608	1.278	2.460	1.039	1.618	3.772*	2.741
Pinot Gris	tgrowingsq	-0.0452	-0.0521	0.0818	0.0528	-0.0252	-0.0680	0.00288	-0.0314	-0.113*	-0.0871
Model 2	tgrowingdiff	0.219***	0.166***	-0.0950	-0.168	0.165*	0.0968	-0.475	-0.560	0.199*	0.0783
	R-squared	0.040	0.056	0.008	0.026	0.025	0.056	0.025	0.060	0.150	0.339
	tgrowing*	17.06	15.99	12.87	15.24	25.31	18.07	-180.4	25.80	16.68	15.73
	tgrowingmax	4.757***	5.639***	-4.009	-3.209	7.105**	8.552***	-3.309	-1.516	10.51**	11.38***
Pinot Gris	tgrowingmaxsq	-0.107**	-0.131***	0.102*	0.0754	-0.162**	-0.200**	0.0886	0.0363	-0.251**	-0.277***
Model 3	R-squared	0.041	0.057	0.009	0.026	0.034	0.067	0.015	0.050	0.184	0.381
	tgrowingmax*	22.26	21.58	19.60	21.28	21.96	21.41	18.67	20.86	20.96	20.54

To summarise the results of Tables 6-8, 56% of our results are consistent with expectation and give a plausible optimal temperature and 27% are also significant when using product-level data. The white varieties do generally better than the red varieties in generating plausible results. This is in direct contrast to Sadras et al. (2007) who found significant results for the Australian red varieties but not the white ones. It is clear that there is no one model that always provides plausible results when using product-level data. The results for the red varieties are generally poor - Syrah and Merlot had their only plausible results for the treatments that limits the sample to wines above $50 and $30, respectively, but Pinot Noir had mildly significant results for the FE model with trend only. The white varieties tend to give the best results when using the OLS model. If just one model was chosen, then the OLS model has the most potential, despite the fact that it is not controlling for the underlying quality the way that the FE model is designed to do. For Pinot Gris, the best results are obtained with the growing season maximum temperature, not the average temperature that works for the other varieties. Last, there seems to be a lot of merit in using a range of models and pick the ones that give plausible results, as we have done here, to allow for the fact that different varieties are best explained with a different model.

The most consistently performing treatment across all varieties is the vintage treatment, where the product-level data is collapsed to vintage-level observations, where all results are consistent with expectation and 53% are statistically significant despite the small sample size. Moreover, the vintage treatment has the best results out of all treatments for Pinot Noir, Sauvignon Blanc, Riesling and Pinot Gris when judged by the significance of the key coefficients and the R^2 score. The vintage treatment gives plausible results for the remaining varieties although not the best using the same criteria. We conclude that there is great potential in using vintage data constructed from expert-rating data for individual wines for climate change research.

Last, we want to apply our predicted optimal temperatures to the current situation in New Zealand. Figure 1 takes the estimated variety-specific optimal temperature band for each variety from Tables 6-8 and compares it to the 2022 predicted temperature for each region from Table 2. The temperature band for each variety is the range of optimal temperature values from the "green" and intage results. The vertical lines represent the forecasted 2022 growing-season average temperatures for the wine regions, found in the last column of Table 2.

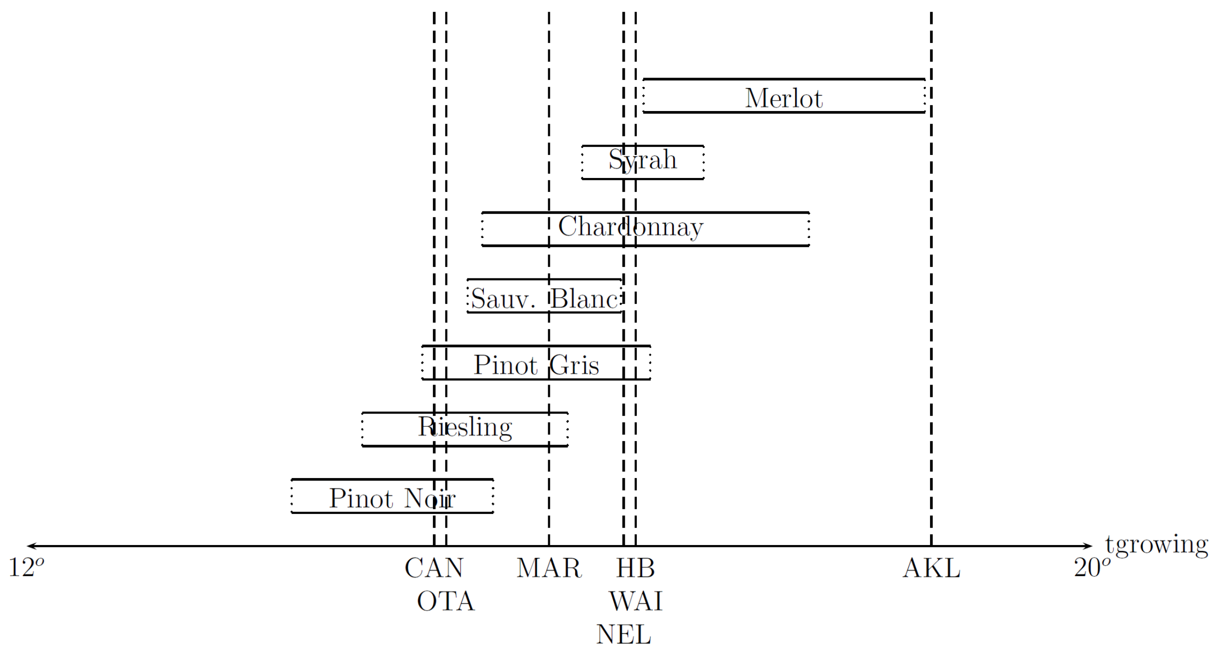

Figure 1: Predicted growing season average temperatures for the wine regions and the optimal growing season temperature bands for each variety.[13]

Figure 1 shows that Pinot Noir and Riesling have an optimal temperature range that fits well the current temperatures of Canterbury and Otago for which these are the most important varieties in the dataset. The current temperatures for these regions is at the bottom end of the optimal range for Pinot Gris. As the temperatures rise, these regions are likely to look at moving away from Pinot Noir production and towards producing more Pinot Gris, Sauvignon Blanc and Chardonnay. Marlborough's climate is optimal for Riesling, Pinot Gris, Sauvignon Blanc and Chardonnay, but it is already too warm to have optimal conditions for Pinot Noir. For Nelson, Wairarapa and Hawkes' Bay, the climate is already too warm for Pinot Noir and Riesling, and getting to be too warm for Sauvignon Blanc. Our results suggest that Pinot Gris, Chardonnay

[13] AKL=Auckland; HB=Hawke's Bay; WAI=Wairarapa; NEL=Nelson; MAR=Marlborough; CAN=Canterbury, OTA=Otago.

and Syrah would thrive in these regions, and the climate will very soon be optimal for Merlot. Given that Syrah and Merlot are currently produced predominantly in Hawke's Bay, this suggests that the other two regions would have potential to successfully switch to these varieties, away from Pinot Noir, Riesling and Sauvignon Blanc. Last, our results indicate that Auckland's average temperature is above the optimal range for all of the wine varieties considered here, possibly with the exception of Merlot that has an upper bound just below the 2022 temperature in Auckland. According to the results of Jones (2015), Auckland should be able to successfully produce Cabernet Sauvignon and Zinfandel, for example. However, due to the small number of observations, these varieties were not included in our dataset so we are unable to verify this. There is also potential for Auckland's Syrah to be successful if it is produced in a style more suitable for a warm climate.

Figure 2 combines the results on the optimal maximum temperature for Pinot Gris from Table 8 and compares that to the 2022 predicted maximum temperature for each region from Table 2. The first thing to note is that the order of regions in terms of the maximum temperature is different from the average temperature. For example, Hawke's Bay and Wairarapa, the second and third northernmost regions in our dataset, respectively, have the coolest maximum temperatures while their average temperatures sat second to only Auckland.

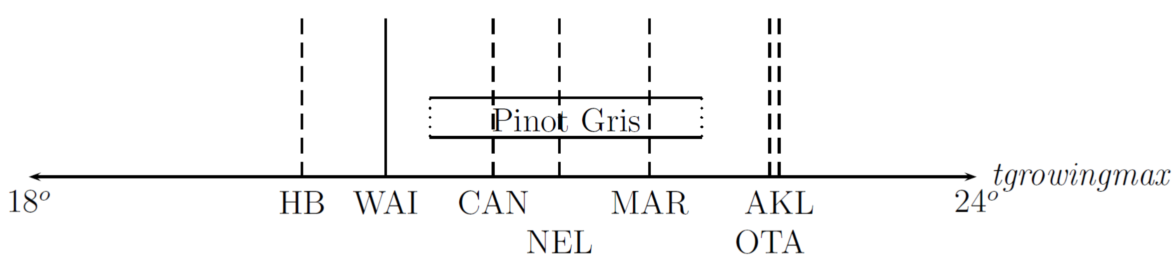

Figure 2: Predicted growing season maximum temperatures for the wine regions and the optimal growing season maximum temperature band for Pinot Gris.[14]

Because of this, the results in Figure 1 and Figure 2 are not fully aligned. The three regions that currently have the optimal maximum temperature for Pinot Gris – Canterbury, Nelson and

[14] AKL=Auckland; HB=Hawke's Bay; WAI=Wairarapa; NEL=Nelson; MAR=Marlborough; CAN=Canterbury, OTA=Otago.

Marlborough, were also included amongst the six regions that had the optimal average temperature for Pinot Gris in Figure 1. However, the maximum temperature in Otago is too high and in Hawke's Bay and Wairarapa's too low, suggesting that Pinot Gris is not a variety that should be planted in Otago and that it will become suitable for Hawke's Bay and Wairarapa as their climates warm up. This change in the ranking of the two temperature variables between the regions explains why Models 1 and 2 did not fit very well with the data even though Model 3 did, and that Figure 2 is most likely the more accurate of the two figures for Pinot Gris.

5. Conclusion

We used individual wine ratings from an extensive list wines rated by Bob Campbell in 2002-2016 to investigate how suitable such a product-level dataset is for climate-change research. We investigated a function that linked the growing-season temperature to the wine quality separately for the seven most rated single-variety wines in the dataset. We had 10-14 treatments for each variety to find out the treatments that provide plausible results. We used the best results to predict an optimal temperature band for each variety. We then compared these predictions to our predictions of the 2022 growing-season temperature to discuss how each region is situated now and in the near future to the varieties it is growing and what would be the most likely candidates for success as the climate continues to warm up.

Our results suggest that, at least for New Zealand, the product-level data has the best success for the white varieties but only limited success for the red varieties. Out of the treatments that we tried, the OLS with and without the trend variable worked the best but it did not work for all varieties. This suggests a need to use a variety of models and treatments to find the best model for each variety to provide accurate temperature maximum predictions. We also found that there is great potential for the use of vintage data, even when specific vintage ratings are not available and the data is collapsed from the product-level data. This produced the best results out of all treatment for four varieties and plausible results, although not significant, for the other.

Our results contribute to the literature that has found that some varieties, or even regions, do not have a clear link between climate and quality. Examples of such studies include, amongst others, Oczkowski (2016) who found a convex relationship between weather and quality for Riesling and Semillon, and Jones *et al*. (2005), who found that the relationship between climate and the quality of wine is “less clear” for the New World wine regions than for the Old World wine regions. While none of our treatments worked for all varieties, with the exception of the vintage treatment, there were always some treatments for each variety that showed a clear positive, concave relationship between the growing season temperature or maximum temperature and the wine quality that had very plausible optimal temperature estimates. It is therefore possible that using a variety of regression models could identify the link between climate and quality for all varieties in all regions.

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Appendix Table 1: Model 1 (top) and Model 2 (bottom) results for Pinot Noir

Model 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
Treatment	all	all	all	all	>=$50	>=$50	>=$50	>=$50	top100	top100	top100	top100	vintage	vintage
tgrowing	1.162	1.738	0.886	3.988	-0.970	2.072	-4.860	-2.127	-13.12***	-12.42***	-5.783	-3.653	9.000**	5.060
	(1.503)	(1.346)	(2.505)	(2.428)	(2.456)	(2.330)	(4.383)	(4.148)	(4.166)	(3.981)	(5.755)	(5.389)	(3.927)	(3.080)
tgrowingsq	-0.0248	-0.0513	-0.00800	-0.143*	0.0503	-0.0588	0.200	0.0725	0.446***	0.417***	0.216	0.114	-0.300**	-0.180*
	(0.0509)	(0.0455)	(0.0826)	(0.0803)	(0.0812)	(0.0773)	(0.144)	(0.137)	(0.135)	(0.129)	(0.187)	(0.176)	(0.122)	(0.0958)
dormantrain	-0.00360***	-0.00343***	0.00118**	9.59e-05	-0.00114*	-0.000608	0.00156*	0.000617	-0.000903	-0.000652	0.000691	0.000383	-0.00363**	-0.00283**
	(0.000417)	(0.000402)	(0.000459)	(0.00045)	(0.00063)	(0.00061)	(0.00081)	(0.00077)	(0.00092)	(0.000930)	(0.000926)	(0.000867)	(0.00176)	(0.00136)
harvestrain	-0.00869***	-0.00928***	0.000997	-0.000681	0.00323	0.00248	0.00609**	0.00235	0.00329	0.00210	0.00400	-0.000514	-0.00462	-0.00534
	(0.00144)	(0.00142)	(0.00125)	(0.00122)	(0.00227)	(0.00221)	(0.00258)	(0.00247)	(0.00313)	(0.00322)	(0.00310)	(0.00298)	(0.00383)	(0.00363)
trend		0.256***		0.224***		0.283***		0.241***		0.151***		0.209***		0.277***
		(0.0144)		(0.0154)		(0.0230)		(0.0249)		(0.0387)		(0.0318)		(0.0400)
Constant	80.09***	75.45***	78.26***	60.93***	96.59***	73.24***	120.2***	106.6***	190.3***	184.9***	131.4***	121.3***	24.01	53.99**
	(11.10)	(9.960)	(18.96)	(18.35)	(18.58)	(17.61)	(33.25)	(31.43)	(32.16)	(30.60)	(44.11)	(41.26)	(31.15)	(24.41)
Observations	4,233	4,233	4,233	4,233	1,073	1,073	1,073	1,073	351	351	351	351	99	99
R-squared	0.043	0.112	0.010	0.077	0.025	0.164	0.041	0.146	0.065	0.115	0.033	0.158	0.248	0.523
tgrowing*	23.39	16.95	55.38	13.99	9.652	17.61	12.18	14.66	14.73	14.88	13.41	16.01	14.98	14.02
Number of pr			1,306	1,306			309	309			55	55		
Model 2	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
Treatment	all	all	all	all	>=$50	>=$50	>=$50	>=$50	top100	top100	top100	top100	vintage	vintage
tgrowing	-3.104*	0.141	0.889	4.014*	-5.207*	2.805	-4.883	-1.786	-15.51***	-11.75**	-6.389	-4.017	10.62***	6.090*
	(1.754)	(1.514)	(2.505)	(2.428)	(3.100)	(2.822)	(4.391)	(4.153)	(4.893)	(4.726)	(5.753)	(5.406)	(3.752)	(3.097)
tgrowingsq	0.122**	0.00403	-0.00923	-0.141*	0.195*	-0.0839	0.200	0.0654	0.525***	0.395**	0.227	0.122	-0.343***	-0.208**
	(0.0596)	(0.0514)	(0.0827)	(0.0803)	(0.104)	(0.0946)	(0.144)	(0.137)	(0.160)	(0.155)	(0.187)	(0.176)	(0.116)	(0.0958)
tgrowingdiff	0.257***	0.0947***	0.0648	-0.139	0.186***	-0.0306	0.0231	-0.279	0.0699	-0.0194	0.435	0.237	0.353***	0.171
	(0.0348)	(0.0351)	(0.118)	(0.114)	(0.0591)	(0.0547)	(0.208)	(0.198)	(0.0703)	(0.0717)	(0.276)	(0.260)	(0.113)	(0.107)
dormantrain	-0.00112**	-0.00253***	0.00121***	2.11e-05	0.000567	-0.000882	0.00158*	0.000401	-0.000321	-0.000810	0.00104	0.000579	-0.000592	-0.00141
	(0.000530)	(0.000528)	(0.000462)	(0.000453)	(0.000786)	(0.000742)	(0.000820)	(0.000782)	(0.00106)	(0.00105)	(0.000950)	(0.000893)	(0.00197)	(0.00166)
harvestrain	-0.00664***	-0.00851***	0.00113	-0.000989	0.00566**	0.00207	0.00615**	0.00163	0.00437	0.00178	0.00493	6.23e-05	-0.00449	-0.00524
	(0.00146)	(0.00146)	(0.00128)	(0.00124)	(0.00241)	(0.00233)	(0.00263)	(0.00252)	(0.00348)	(0.00350)	(0.00315)	(0.00304)	(0.00359)	(0.00354)
trend		0.244***		0.226***		0.287***		0.246***		0.153***		0.205***		0.259***
		(0.0151)		(0.0155)		(0.0239)		(0.0252)		(0.0407)		(0.0320)		(0.0422)
Constant	107.0***	85.57***	77.73***	61.88***	124.6***	68.35***	120.2***	106.5***	207.1***	180.2***	133.0***	122.4***	4.482	42.66*
	(12.69)	(10.95)	(18.98)	(18.36)	(22.62)	(20.65)	(33.28)	(31.41)	(36.87)	(35.50)	(44.01)	(41.28)	(29.92)	(24.91)
Observations	4,233	4,233	4,233	4,233	1,073	1,073	1,073	1,073	351	351	351	351	99	99
R-squared	0.056	0.114	0.010	0.077	0.034	0.164	0.041	0.148	0.068	0.115	0.041	0.160	0.312	0.537
tgrowing*	12.71	-17.51	48.18	14.21	13.35	16.71	12.21	13.65	14.77	14.88	14.09	16.48	15.50	14.62
Number of pr			1,306	1,306			309	309			55	55		

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2: Model 1 (top) and Model 2 (bottom) results for Syrah

Model 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
Treatment	all	all	all	all	>=$50	>=$50	>=$50	>=$50	top100	top100	top100	top100	vintage	vintage
tgrowing	4.627	3.081	-0.548	-1.613	12.55***	10.73**	-12.28	-12.96*	53.27	44.44	26.52	17.52	7.188	7.322
	(2.994)	(3.000)	(5.453)	(5.412)	(4.736)	(4.841)	(7.433)	(7.260)	(43.01)	(41.87)	(26.92)	(24.38)	(6.057)	(6.019)
tgrowingsq	-0.129	-0.0867	0.0354	0.0516	-0.382***	-0.332**	0.407*	0.401*	-1.628	-1.358	-0.796	-0.574	-0.210	-0.220
	(0.0908)	(0.0907)	(0.169)	(0.168)	(0.141)	(0.145)	(0.230)	(0.224)	(1.352)	(1.315)	(0.855)	(0.773)	(0.186)	(0.183)
dormantrain	-9.61e-05	0.000931	0.00152	0.00160	0.00270	0.00321*	0.000538	0.000286	0.00595*	0.00622*	0.00284	0.00225	0.00329	0.00439**
	(0.00120)	(0.00122)	(0.00104)	(0.00103)	(0.00169)	(0.00172)	(0.00149)	(0.00145)	(0.00333)	(0.00351)	(0.00198)	(0.00179)	(0.00210)	(0.00208)
harvestrain	-0.00999***	-0.00861***	-0.00302	-0.00318	-0.00873**	-0.00727	0.000140	-0.000634	-0.0108	-0.0102	-0.00734	-0.00492	-0.00880*	-0.00847
	(0.00254)	(0.00258)	(0.00209)	(0.00208)	(0.00431)	(0.00442)	(0.00345)	(0.00337)	(0.0109)	(0.0109)	(0.00563)	(0.00512)	(0.00514)	(0.00513)
trend		0.155***		0.119***		0.148***		0.159***		0.0764		0.251***		0.245***
		(0.0352)		(0.0361)		(0.0559)		(0.0489)		(0.101)		(0.0713)		(0.0665)
Constant	50.68**	62.83**	90.01**	102.0**	-9.686	4.870	184.8***	196.3***	-342.3	-270.9	-126.5	-41.39	28.49	26.38
	(24.55)	(24.65)	(43.90)	(43.65)	(39.33)	(40.14)	(60.14)	(58.82)	(342.5)	(333.2)	(211.9)	(192.3)	(48.97)	(49.03)
Observations	851	851	851	851	292	292	292	292	61	61	61	61	77	77
R-squared	0.031	0.054	0.018	0.037	0.044	0.075	0.037	0.087	0.261	0.270	0.143	0.319	0.122	0.253
tgrowing*	17.98	17.77	7.742	15.63	16.41	16.17	15.09	16.15	16.36	16.36	16.66	15.25	17.08	16.66
Number of pr			309	309			93	93			8	8		

Model 2	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
Treatment	all	all	all	all	>=$50	>=$50	>=$50	>=$50	top100	top100	top100	top100	vintage	vintage
tgrowing	2.387	-0.569	-0.617	-1.529	7.560	4.253	-12.21	-12.91*	59.70	34.16	26.41	17.23	6.036	4.273
	(3.328)	(3.348)	(5.469)	(5.426)	(5.134)	(5.530)	(7.428)	(7.274)	(36.90)	(31.36)	(26.99)	(24.63)	(6.314)	(6.304)
tgrowingsq	-0.0609	0.0232	0.0370	0.0495	-0.232	-0.137	0.397*	0.397*	-1.865	-1.092	-0.800	-0.565	-0.177	-0.132
	(0.101)	(0.101)	(0.170)	(0.168)	(0.153)	(0.165)	(0.230)	(0.225)	(1.164)	(0.988)	(0.857)	(0.780)	(0.193)	(0.191)
tgrowingdiff	-0.123*	-0.193***	0.0548	-0.0760	-0.289***	-0.356***	0.569	0.251	-0.585***	-0.690***	0.550	-0.203	-0.112	-0.300**
	(0.0728)	(0.0736)	(0.283)	(0.283)	(0.102)	(0.106)	(0.507)	(0.507)	(0.0772)	(0.0809)	(0.637)	(0.619)	(0.127)	(0.134)
dormantrain	-0.000467	0.000454	0.00151	0.00161	0.00148	0.00180	0.000357	0.000214	0.00167	0.00173	0.00291	0.00220	0.00264	0.00279
	(0.00122)	(0.00123)	(0.00105)	(0.00104)	(0.00163)	(0.00162)	(0.00150)	(0.00146)	(0.00278)	(0.00245)	(0.00199)	(0.00181)	(0.00218)	(0.00221)
harvestrain	-0.0102***	-0.00884***	-0.00293	-0.00331	-0.00894**	-0.00725*	0.000654	-0.000382	-0.00692	-0.00431	-0.00711	-0.00491	-0.00872*	-0.00820
	(0.00252)	(0.00255)	(0.00215)	(0.00213)	(0.00425)	(0.00438)	(0.00347)	(0.00342)	(0.00649)	(0.00558)	(0.00565)	(0.00516)	(0.00515)	(0.00506)
trend		0.170***		0.121***		0.176***		0.154***		0.231**		0.260***		0.277***
		(0.0358)		(0.0365)		(0.0565)		(0.0501)		(0.0938)		(0.0771)		(0.0685)
Constant	70.23**	94.55***	90.30**	101.8**	34.23	61.63	182.2***	194.8***	-378.0	-168.9	-128.3	-37.60	39.63	55.78
	(27.59)	(27.80)	(43.96)	(43.70)	(42.99)	(46.27)	(60.14)	(59.01)	(293.0)	(248.7)	(212.4)	(194.5)	(51.78)	(52.11)
Observations	851	851	851	851	292	292	292	292	61	61	61	61	77	77
R-squared	0.034	0.061	0.018	0.037	0.068	0.110	0.043	0.088	0.518	0.590	0.156	0.320	0.126	0.282

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3: Model 1 (top) and Model 2 (bottom) results for Chardonnay

Model 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
Treatment	all	all	all	all	>=$50	>=$50	>=$50	>=$50	top100	top100	top100	top100	vintage	vintage
tgrowing	4.932***	3.742***	6.122**	5.996**	9.441**	9.086**	16.97**	16.08**	-0.998	-1.419	4.908	3.834	4.668	2.748
	(1.341)	(1.297)	(2.708)	(2.669)	(4.465)	(4.103)	(7.762)	(7.234)	(3.206)	(3.157)	(6.839)	(6.585)	(3.484)	(2.366)
tgrowingsq	-0.143***	-0.116***	-0.179**	-0.196**	-0.272**	-0.273**	-0.491**	-0.502**	0.0379	0.0460	-0.144	-0.139	-0.139	-0.0883
	(0.0423)	(0.0409)	(0.0853)	(0.0841)	(0.136)	(0.125)	(0.237)	(0.221)	(0.0983)	(0.0967)	(0.217)	(0.208)	(0.108)	(0.0732)
dormantrain	-0.0016***	-0.000767	0.00156***	0.00111**	-0.00485***	-0.00268*	0.00183	0.00177	-0.00113	-0.000486	-0.000161	-0.000289	-0.000231	0.000872
	(0.000551)	(0.000533)	(0.000565)	(0.000561)	(0.00158)	(0.00147)	(0.00149)	(0.00139)	(0.00136)	(0.00140)	(0.00143)	(0.00138)	(0.00147)	(0.00109)
harvestrain	-0.00308**	-0.00303**	-0.00203*	-0.00240**	-0.00188	-0.00148	-0.00639	-0.00756**	0.00162	0.00194	-0.000985	-0.00218	-0.00225	-0.00327
	(0.00144)	(0.00139)	(0.00120)	(0.00118)	(0.00406)	(0.00380)	(0.00391)	(0.00365)	(0.00367)	(0.00345)	(0.00382)	(0.00369)	(0.00365)	(0.00236)
trend		0.241***		0.133***		0.335***		0.242***		0.146***		0.174***		0.306***
		(0.0169)		(0.0189)		(0.0540)		(0.0519)		(0.0554)		(0.0485)		(0.0294)
Constant	48.89***	58.70***	37.53*	43.02**	14.88	17.01	-52.22	-36.83	100.9***	104.0***	52.90	67.45	51.52*	66.70***
	(10.60)	(10.26)	(21.48)	(21.19)	(36.49)	(33.44)	(63.45)	(59.21)	(25.94)	(25.53)	(53.90)	(52.01)	(27.79)	(18.95)
Observations	2,518	2,518	2,518	2,518	217	217	217	217	177	177	177	177	105	105
R-squared	0.013	0.087	0.013	0.042	0.050	0.224	0.079	0.206	0.010	0.071	0.008	0.089	0.034	0.517
tgrowing*	17.20	16.18	17.12	15.32	17.34	16.64	17.29	16.02	13.15	15.43	17.09	13.77	16.84	15.56
Number of pr			859	859			77	77			27	27		
Model 2	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
Treatment	all	all	all	all	>=$50	>=$50	>=$50	>=$50	top100	top100	top100	top100	vintage	vintage
tgrowing	5.734***	4.263***	5.930**	6.283**	15.70***	13.16***	14.07*	14.74*	-1.144	-1.443	1.863	1.953	6.077*	2.908
	(1.321)	(1.288)	(2.743)	(2.704)	(4.066)	(4.026)	(7.972)	(7.474)	(3.165)	(3.147)	(6.909)	(6.704)	(3.267)	(2.400)
tgrowingsq	-0.165***	-0.130***	-0.174**	-0.204**	-0.456***	-0.392***	-0.413*	-0.465**	0.0457	0.0489	-0.0623	-0.0868	-0.178*	-0.0927
	(0.0417)	(0.0406)	(0.0862)	(0.0850)	(0.123)	(0.122)	(0.242)	(0.227)	(0.0969)	(0.0962)	(0.218)	(0.211)	(0.101)	(0.0739)
tgrowingdiff	0.206***	0.119***	0.0677	-0.102	0.322***	0.209**	0.787	0.369	0.184*	0.0897	0.858**	0.558	0.269***	0.0266
	(0.0336)	(0.0337)	(0.153)	(0.153)	(0.0919)	(0.0830)	(0.531)	(0.507)	(0.0940)	(0.0856)	(0.404)	(0.404)	(0.0908)	(0.0859)
dormantrain	0.000468	0.000403	0.00156***	0.00110**	-0.00237	-0.00117	0.00166	0.00169	0.000340	0.000157	-0.000137	-0.000262	0.00220	0.00110
	(0.000643)	(0.000629)	(0.000565)	(0.000561)	(0.00158)	(0.00147)	(0.00149)	(0.00140)	(0.00140)	(0.00132)	(0.00142)	(0.00137)	(0.00169)	(0.00142)
harvestrain	-0.00302**	-0.00300**	-0.00195	-0.00252**	-0.00200	-0.00158	-0.00544	-0.00708*	0.00282	0.00249	0.000244	-0.00127	-0.00185	-0.00322
	(0.00144)	(0.00139)	(0.00121)	(0.00120)	(0.00395)	(0.00375)	(0.00394)	(0.00371)	(0.00372)	(0.00349)	(0.00382)	(0.00373)	(0.00354)	(0.00233)
trend		0.230***		0.135***		0.319***		0.235***		0.129**		0.157***		0.303***
		(0.0173)		(0.0191)		(0.0537)		(0.0529)		(0.0542)		(0.0498)		(0.0334)
Constant	38.87***	52.42***	38.64*	41.44*	-41.86	-19.92	-32.58	-28.07	98.73***	102.6***	72.04	78.54	35.49	64.95***
	(10.50)	(10.25)	(21.63)	(21.32)	(33.50)	(33.18)	(64.55)	(60.52)	(25.86)	(25.70)	(54.02)	(52.46)	(26.27)	(19.55)
Observations	2,518	2,518	2,518	2,518	217	217	217	217	177	177	177	177	105	105
R-squared	0.026	0.091	0.013	0.042	0.084	0.238	0.093	0.209	0.035	0.076	0.038	0.101	0.092	0.518
tgrowing*	17.37	16.45	17.08	15.42	17.20	16.77	17.03	15.86	12.52	14.76	14.95	11.26	17.10	15.68
Number of pr			859	859			77	77			27	27		

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 4: Model 1 (top) and Model 2 (bottom) results for Merlot

Model 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
Treatment	all	all	all	all	>=$30	>=$30	>=$30	>=$30	vintage	vintage
tgrowing	7.447	1.995	-0.234	-2.159	17.01**	10.25	11.86	20.00	7.910	6.332
	(5.176)	(5.195)	(10.01)	(9.952)	(8.081)	(7.902)	(21.83)	(21.70)	(6.100)	(5.852)
tgrowingsq	-0.213	-0.0536	0.0351	0.0756	-0.510**	-0.313	-0.308	-0.589	-0.220	-0.174
	(0.160)	(0.159)	(0.313)	(0.310)	(0.248)	(0.242)	(0.680)	(0.678)	(0.190)	(0.182)
dormantrain	0.00166	0.00253*	0.00217	0.00212	0.00107	0.00261	0.00548	0.00592*	-0.00469*	-0.00518*
	(0.00143)	(0.00148)	(0.00178)	(0.00176)	(0.00235)	(0.00237)	(0.00331)	(0.00325)	(0.00279)	(0.00308)
harvestrain	0.000380	-1.23e-05	0.00211	0.00161	-0.00602	-0.00701	0.000281	-0.000730	-0.00680	-0.00964
	(0.00297)	(0.00297)	(0.00299)	(0.00297)	(0.00500)	(0.00516)	(0.00548)	(0.00538)	(0.00591)	(0.00632)
trend		0.189***		0.124**		0.270***		0.192**		0.146**
		(0.0399)		(0.0523)		(0.0659)		(0.0916)		(0.0703)
Constant	22.62	67.57	81.54	101.3	-51.11	4.027	-23.80	-82.94	20.23	33.09
	(41.79)	(42.05)	(80.22)	(79.93)	(65.46)	(64.02)	(175.3)	(173.7)	(48.79)	(46.85)
Observations	484	484	484	484	157	157	157	157	54	54
R-squared	0.031	0.077	0.025	0.046	0.057	0.154	0.109	0.160	0.136	0.206
tgrowing*	17.52	18.62	3.333	14.28	16.66	16.39	19.24	16.98	17.95	18.18
Number of pr			226	226			80	80		
Model 2	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
Treatment	all	all	all	all	>=$30	>=$30	>=$30	>=$30	vintage	vintage
tgrowing	7.347	0.580	-4.026	-4.868	18.90**	11.03	-10.93	-0.0262	7.115	3.853
	(5.383)	(5.489)	(10.16)	(10.11)	(8.485)	(8.337)	(24.26)	(24.73)	(6.234)	(6.221)
tgrowingsq	-0.209	-0.0103	0.147	0.158	-0.568**	-0.336	0.389	0.0283	-0.198	-0.103
	(0.166)	(0.169)	(0.317)	(0.315)	(0.261)	(0.255)	(0.753)	(0.770)	(0.194)	(0.192)
tgrowingdiff	-0.00565	-0.0724	0.832*	0.647	0.112	0.0431	1.859**	1.529	-0.0983	-0.260
	(0.0895)	(0.0936)	(0.443)	(0.449)	(0.162)	(0.163)	(0.932)	(0.939)	(0.155)	(0.159)
dormantrain	0.00161	0.00186	0.00150	0.00160	0.00181	0.00288	0.00290	0.00373	-0.00512*	-0.00645**
	(0.00181)	(0.00185)	(0.00181)	(0.00180)	(0.00264)	(0.00257)	(0.00350)	(0.00348)	(0.00275)	(0.00289)
harvestrain	0.000383	5.45e-06	0.00323	0.00254	-0.00587	-0.00695	0.00354	0.00211	-0.00622	-0.00879
	(0.00297)	(0.00297)	(0.00303)	(0.00303)	(0.00503)	(0.00517)	(0.00562)	(0.00560)	(0.00601)	(0.00616)
trend		0.193***		0.109**		0.268***		0.161*		0.181***
		(0.0401)		(0.0533)		(0.0653)		(0.0925)		(0.0670)
Constant	23.49	79.95*	107.4	119.0	-67.74	-2.738	149.2	68.68	28.09	56.95
	(43.78)	(44.81)	(81.00)	(80.70)	(69.36)	(68.16)	(192.5)	(195.3)	(50.36)	(50.76)
Observations	484	484	484	484	157	157	157	157	54	54
R-squared	0.031	0.078	0.038	0.054	0.060	0.155	0.155	0.190	0.140	0.236
tgrowing*	17.54	28.27	13.69	15.45	16.63	16.39	14.06	0.462	18	18.74
Number of pr			226	226			80	80		

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 5: Model 1 (top) and Model 2 (bottom) results for Sauvignon Blanc

Model 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
VARIABLES	all	all	all	all	>=$30	>=$30	>=$30	>=$30	vintage	vintage
tgrowing	14.34***	11.76***	1.174	5.807	25.65***	24.16***	-10.52	11.51	9.286***	7.728**
	(1.827)	(1.813)	(4.234)	(4.186)	(4.929)	(4.882)	(18.29)	(17.77)	(3.482)	(3.100)
tgrowingsq	-0.451***	-0.381***	-0.0179	-0.191	-0.813***	-0.784***	0.365	-0.383	-	-0.252**
	(0.0583)	(0.0576)	(0.137)	(0.136)	(0.155)	(0.153)	(0.596)	(0.580)	(0.109)	(0.0973)
dormantrain	-	-	0.000485	1.79e-06	-	-	0.000262	-	-0.00112	0.000166
	(0.000455)	(0.000443)	(0.000439	(0.000434	(0.00107)	(0.00101)	(0.00110	(0.00104)	(0.00136)	(0.000994
harvestrain	-	-	-0.00181	-0.00220*	-0.00232	-0.00795**	-0.00191	-0.00407	-0.00151	-0.00287
	(0.00128)	(0.00122)	(0.00114)	(0.00112)	(0.00457)	(0.00404)	(0.00400	(0.00381)	(0.00365)	(0.00227)
trend		0.246***		0.166***		0.403***		0.267***		0.292***
		(0.0170)		(0.0184)		(0.0443)		(0.0490)		(0.0355)
Constant	-22.56	-1.450	75.64**	44.43	-108.5***	-95.67**	167.1	3.765	15.69	28.02
	(14.31)	(14.22)	(32.75)	(32.32)	(39.28)	(38.85)	(140.2)	(136.1)	(27.66)	(24.45)
Observations	3,087	3,087	3,087	3,087	421	421	421	421	99	99
R-squared	0.028	0.092	0.009	0.046	0.075	0.241	0.013	0.119	0.107	0.518
tgrowing*	15.88	15.43	32.83	15.19	15.77	15.40	14.42	15.01	15.95	15.31
Number of			977	977			170	170		
Model 2	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
VARIABLES	all	all	all	all	>=$30	>=$30	>=$30	>=$30	vintage	vintage
tgrowing	10.71***	9.562***	0.593	5.447	22.32***	22.35***	-10.17	12.91	11.22***	8.727***
	(1.911)	(1.856)	(4.298)	(4.252)	(4.853)	(4.625)	(18.54)	(18.04)	(3.654)	(3.225)
tgrowingsq	-0.325***	-0.301***	-0.00189	-0.181	-0.698***	-0.718***	0.355	-0.424	-	-0.282***
	(0.0612)	(0.0591)	(0.138)	(0.137)	(0.152)	(0.145)	(0.602)	(0.587)	(0.114)	(0.101)
tgrowingdiff	0.418***	0.309***	0.119	0.0718	0.561***	0.349***	-0.0458	-0.168	0.282***	0.136*
	(0.0305)	(0.0310)	(0.151)	(0.148)	(0.0767)	(0.0700)	(0.368)	(0.349)	(0.0981)	(0.0691)
dormantrain	0.000427	-4.08e-05	0.000536	3.39e-05	0.000368	-0.000378	0.000235	-	0.00205	0.00163
	(0.000482)	(0.000479)	(0.000444	(0.000439	(0.00104)	(0.00101)	(0.00112	(0.00106)	(0.00150)	(0.00114)
harvestrain	-0.00283**	-	-0.00153	-0.00203*	0.00165	-0.00446	-0.00205	-0.00456	-0.00114	-0.00263
	(0.00126)	(0.00122)	(0.00119)	(0.00117)	(0.00436)	(0.00400)	(0.00415	(0.00395)	(0.00363)	(0.00228)
trend		0.199***		0.166***		0.331***		0.269***		0.279***
		(0.0176)		(0.0184)		(0.0454)		(0.0491)		(0.0352)
Constant	-2.375	9.470	79.53**	46.84	-92.72**	-88.15**	164.6	-6.302	-4.381	17.83
	(14.89)	(14.51)	(33.12)	(32.71)	(38.70)	(36.96)	(142.0)	(137.9)	(29.32)	(25.53)
Observations	3,087	3,087	3,087	3,087	421	421	421	421	99	99
R-squared	0.079	0.118	0.009	0.046	0.179	0.276	0.013	0.120	0.177	0.533
tgrowing*	16.46	15.87	156.8	15.04	15.99	15.57	14.33	15.22	16.08	15.48
Number of			977	977			170	170		

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 6: Model 1 (top) and Model 2 (bottom) results for Riesling

Model 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
VARIABLES	all	all	all	all	>=$30	>=$30	>=$30	>=$30	vintage	vintage
tgrowing	4.602**	6.485***	-0.880	4.314	6.207	9.035**	-6.629	-0.772	21.00***	14.63***
	(2.134)	(1.899)	(4.272)	(4.183)	(4.372)	(4.266)	(10.90)	(10.13)	(4.555)	(3.160)
tgrowingsq	-0.143**	-0.215***	0.0565	-0.143	-0.187	-0.291**	0.255	0.0218	-0.702***	-0.504***
	(0.0721)	(0.0644)	(0.141)	(0.138)	(0.145)	(0.141)	(0.361)	(0.336)	(0.147)	(0.102)
dormantrain	-0.00203***	-0.00148***	0.00212***	0.00112*	-0.000722	-0.000282	0.00144	0.000262	-0.00137	-0.000171
	(0.000584)	(0.000556)	(0.000630)	(0.000621)	(0.000978)	(0.000953)	(0.00120)	(0.00113)	(0.00169)	(0.00109)
harvestrain	-0.00440**	-0.00463**	-0.00238	-0.00295*	0.00167	0.00267	0.00120	-0.00111	0.00100	-0.00221
	(0.00193)	(0.00181)	(0.00169)	(0.00164)	(0.00351)	(0.00332)	(0.00357)	(0.00332)	(0.00422)	(0.00240)
trend		0.314***		0.207***		0.255***		0.302***		0.360***
		(0.0209)		(0.0235)		(0.0394)		(0.0425)		(0.0325)
Constant	54.80***	40.38***	90.29***	56.32*	41.91	20.90	134.0	97.13	-65.88*	-17.74
	(15.81)	(14.04)	(32.37)	(31.62)	(32.98)	(32.20)	(82.17)	(76.30)	(35.06)	(24.42)
Observations	1,870	1,870	1,870	1,870	478	478	478	478	94	94
R-squared	0.019	0.128	0.023	0.082	0.026	0.116	0.033	0.173	0.241	0.694
tgrowing*	16.06	15.06	7.788	15.11	16.61	15.50	12.99	17.72	14.95	14.52
Number of pr			661	661			174	174		
Model 2	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
VARIABLES	all	all	all	all	>=$30	>=$30	>=$30	>=$30	vintage	vintage
tgrowing	-1.118	3.869*	-1.004	4.202	1.613	6.974	-6.719	-0.903	18.68***	14.24***
	(2.364)	(2.070)	(4.271)	(4.185)	(4.420)	(4.515)	(10.92)	(10.15)	(4.819)	(3.318)
tgrowingsq	0.0541	-0.125*	0.0553	-0.142	-0.0305	-0.221	0.260	0.0286	-0.619***	-0.489***
	(0.0801)	(0.0704)	(0.141)	(0.138)	(0.147)	(0.150)	(0.362)	(0.337)	(0.157)	(0.107)
tgrowingdiff	0.391***	0.168***	0.261	0.164	0.265***	0.110	-0.0724	-0.109	0.313***	0.0730
	(0.0484)	(0.0475)	(0.183)	(0.178)	(0.0866)	(0.0842)	(0.340)	(0.315)	(0.116)	(0.0690)
dormantrain	0.00149**	-1.64e-05	0.00222***	0.00119*	0.00168	0.000690	0.00140	0.000204	0.00173	0.000526
	(0.000699)	(0.000687)	(0.000634)	(0.000626)	(0.00121)	(0.00121)	(0.00122)	(0.00114)	(0.00207)	(0.00132)
harvestrain	-0.00226	-0.00369**	-0.00181	-0.00259	0.00347	0.00336	0.000945	-0.00150	0.00166	-0.00198
	(0.00194)	(0.00183)	(0.00174)	(0.00169)	(0.00355)	(0.00339)	(0.00377)	(0.00351)	(0.00418)	(0.00244)
trend		0.288***		0.206***		0.241***		0.302***		0.352***
		(0.0220)		(0.0235)		(0.0407)		(0.0425)		(0.0328)
Constant	90.22***	56.82***	89.40***	55.99*	71.50**	34.33	135.2	98.89	-54.46	-16.14
	(17.21)	(15.03)	(32.36)	(31.63)	(32.70)	(33.53)	(82.49)	(76.58)	(36.35)	(25.26)
Observations	1,870	1,870	1,870	1,870	478	478	478	478	94	94
R-squared	0.053	0.134	0.024	0.083	0.045	0.119	0.033	0.173	0.296	0.697
tgrowing*	10.34	15.54	9.076	14.78	26.46	15.79	12.93	15.77	15.10	14.56
Number of pr			661	661			174	174		

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 7: Model 1 (top) and Model 2 (middle) and Model 3 (bottom) results for Pinot Gris

Model 1	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
VARIABLES	all	all	all	all	>=$30	>=$30	>=$30	>=$30	vintage	vintage
tgrowing	2.230*	2.178*	-2.200	-1.781	1.857	2.871	1.948	2.665	2.639	2.282
	(1.226)	(1.157)	(2.921)	(2.898)	(1.815)	(1.816)	(4.736)	(4.673)	(2.292)	(1.959)
tgrowingsq	-0.0725*	-0.0727*	0.0828	0.0549	-0.0478	-0.0839	-0.0366	-0.0765	-0.0815	-0.0745
	(0.0398)	(0.0376)	(0.0932)	(0.0926)	(0.0582)	(0.0584)	(0.149)	(0.148)	(0.0740)	(0.0618)
dormantrain	-0.0021***	-0.0019***	0.00111*	0.000915	-0.00053	-0.00032	-0.00007	-0.00027	-0.0032**	-0.00283**
	(0.000553)	(0.000548)	(0.000610	(0.000607)	(0.0011)	(0.00113)	(0.0012)	(0.00118)	(0.00130)	(0.00127)
harvestrain	-0.00433**	-0.0055***	-0.00283*	-0.0036**	-0.00115	-0.00298	-0.00271	-0.00493	-0.00441	-0.00592**
	(0.00172)	(0.00168)	(0.00167)	(0.00166)	(0.0038)	(0.00380)	(0.0036)	(0.00361)	(0.00339)	(0.00279)
trend		0.146***		0.119***		0.182***		0.144***		0.193***
		(0.0227)		(0.0265)		(0.0473)		(0.0489)		(0.0420)
Constant	73.81***	73.45***	103.7***	103.0***	74.84***	66.34***	70.69*	68.19*	69.87***	72.30***
	(9.455)	(8.919)	(22.89)	(22.70)	(14.14)	(14.13)	(37.54)	(37.00)	(17.71)	(15.34)
Observations	1,778	1,778	1,778	1,778	374	374	374	374	102	102
R-squared	0.023	0.047	0.008	0.025	0.015	0.052	0.020	0.052	0.115	0.334
tgrowing*	15.39	14.97	13.29	16.21	19.41	17.12	26.62	17.42	16.20	15.33
Number of pr			603	603			114	114		
Model 2	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
VARIABLES	all	all	all	all	>=$30	>=$30	>=$30	>=$30	vintage	vintage
tgrowing	1.543	1.665	-2.106	-1.608	1.278	2.460	1.039	1.618	3.772*	2.741
	(1.198)	(1.150)	(2.928)	(2.906)	(1.812)	(1.811)	(4.790)	(4.718)	(2.069)	(1.847)
tgrowingsq	-0.0452	-0.0521	0.0818	0.0528	-0.0252	-0.0680	0.00288	-0.0314	-0.113*	-0.0871
	(0.0389)	(0.0374)	(0.0932)	(0.0927)	(0.0583)	(0.0584)	(0.152)	(0.150)	(0.0670)	(0.0585)
tgrowingdiff	0.219***	0.166***	-0.0950	-0.168	0.165*	0.0968	-0.475	-0.560	0.199*	0.0783
	(0.0398)	(0.0413)	(0.195)	(0.194)	(0.0847)	(0.0856)	(0.390)	(0.385)	(0.105)	(0.102)
dormantrain	-0.000271	-0.000527	0.00106*	0.000826	0.000822	0.000459	-0.00028	-0.00052	-0.00142	-0.00214
	(0.000668)	(0.000673)	(0.00062)	(0.000616)	(0.0014)	(0.00138)	(0.0012)	(0.00119)	(0.00161)	(0.00169)
harvestrain	-0.00327*	-0.0045***	-0.00303*	-0.0040**	0.000570	-0.00184	-0.00344	-0.00586	-0.00410	-0.00574**
	(0.00172)	(0.00171)	(0.00172)	(0.00172)	(0.0039)	(0.00387)	(0.0036)	(0.00366)	(0.00338)	(0.00283)
trend		0.123***		0.121***		0.169***		0.149***		0.185***
		(0.0234)		(0.0265)		(0.0478)		(0.0490)		(0.0431)
Constant	74.78***	74.25***	103.5***	102.7***	75.98***	67.62***	80.53**	79.72**	57.26***	67.25***
	(9.215)	(8.834)	(22.90)	(22.71)	(14.05)	(14.01)	(38.37)	(37.76)	(15.95)	(14.49)
Observations	1,778	1,778	1,778	1,778	374	374	374	374	102	102
R-squared	0.040	0.056	0.008	0.026	0.025	0.056	0.025	0.060	0.150	0.339
tgrowing*	17.06	15.99	12.87	15.24	25.31	18.07	-180.4	25.80	16.68	15.73
Number of pr			603	603			114	114		
Model 3	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS	OLS trend	FE	FE trend	OLS	OLS trend	FE	FE trend	OLS	OLS trend
VARIABLES	all	all	all	all	>=$30	>=$30	>=$30	>=$30	vintage	vintage
tgrowingmax	4.757***	5.639***	-4.009	-3.209	7.105**	8.552***	-3.309	-1.516	10.51**	11.38***
	(1.759)	(1.720)	(2.488)	(2.474)	(3.217)	(3.242)	(4.462)	(4.429)	(4.316)	(3.840)
tgrowingmaxsq	-0.107**	-0.131***	0.102*	0.0754	-0.162**	-0.200**	0.0886	0.0363	-0.251**	-0.277***
	(0.0426)	(0.0417)	(0.0599)	(0.0597)	(0.0774)	(0.0781)	(0.106)	(0.106)	(0.106)	(0.0947)
dormantrain	-0.00146***	-0.00174***	0.00124**	0.000946	0.00110	0.000538	0.000200	-0.000149	-0.00242**	-0.00296***
	(0.000561)	(0.000562)	(0.00061)	(0.00061)	(0.0011)	(0.00113)	(0.0012)	(0.00119)	(0.00111)	(0.000976)
harvestrain	-0.00408**	-0.0053***	-0.00303*	-0.0040**	0.000899	-0.00111	-0.00269	-0.00494	-0.00360	-0.00549**
	(0.00169)	(0.00167)	(0.00168)	(0.00168)	(0.0036)	(0.00360)	(0.00360)	(0.00362)	(0.00320)	(0.00261)
trend		0.128***		0.120***		0.175***		0.152***		0.188***
		(0.0235)		(0.0264)		(0.0481)		(0.0495)		(0.0431)
Constant	38.11**	29.21*	128.5***	122.7***	13.77	-0.929	122.2***	106.6**	-19.08	-26.78
	(18.08)	(17.65)	(25.83)	(25.65)	(33.28)	(33.53)	(46.86)	(46.38)	(44.04)	(38.87)
Observations	1,778	1,778	1,778	1,778	374	374	374	374	102	102
R-squared	0.041	0.057	0.009	0.026	0.034	0.067	0.015	0.050	0.184	0.381
tgrowingmax*	22.26	21.58	19.60	21.28	21.96	21.41	18.67	20.86	20.96	20.54
Number of pr			603	603			114	114		

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1